OPTIMAL DESIGN OF DISTRIBUTED ENERGY RESOURCE SYSTEMS UNDER LARGE-SCALE UNCERTAINTIES IN ENERGY DEMANDS BASED ON DECISION-MAKING THEORY

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This study focuses on the optimal design of distributed energy resource (DER) systems with consideration of large-scale uncertainty of energy demands based on decision-making theory. Five integrated modeling and optimization frameworks are developed through the combined use of mixed integer linear programming (MILP) and uncertainty decision-making criteria (including optimistic criterion, pessimistic criterion, Hurwicz criterion, Laplace criterion, and minimax regret criterion). Superstructure-based MILP models are used for the optimal design and optimal operation of the system where the objective function is to minimize the annual cost. The uncertainty of energy demands is represented by assuming a set of possible scenarios. The proposed methods are applied to the planning of a DER system for a hotel in Guangzhou, China and their validity and effectiveness are verified. Results show that each method has its specific feature. Optimistic method is risky and recommends a relative small-scale system, while pessimistic method is conservative presenting a relative large-scale system. Hurwicz method is with great subjectivity, making different decisions at different values of optimism coefficient. Both Laplace method and minimax regret method identify a moderate-scale system as the best alternative. Sensitivity analyses on the energy demand scenarios are conducted and results show that the five methods have high sensitivity to the choice of scenarios.

Key words: *distributed energy resource; mixed integer linear programming; optimal design; optimal operation; uncertainty; uncertain decision-making*

1. Introduction

As an electricity-generation system located in or near end users, distributed energy resource (DER) systems can simultaneously provide electricity, cooling, and heating to meet the demands of local users [1]. They allow for the achievement of high overall efficiency, excellent environmental performance, low transmission and distribution losses, and other benefits through the efficient utilization of exhaust heat and on-site generation [2-4].

However, many types of uncertainties exist in the optimal design of DER systems. Various efforts have been made to assess the uncertainties in the modeling of DER systems. Li et al. [5] conducted sensitivity analyses about energy demands which are described by adopting average, uncertainty and historical peaks. In our previous work, Monte Carlo simulation has been used to evaluate DER systems from the perspective of energy, economic, and environmental aspects under the uncertainties of load demands and energy prices [6]. Zhou et al. [7] developed a two-stage stochastic programming model for the optimal design of DER systems under uncertain load demands and renewable energy supply presented by probability distributions. When taking into account large-scale uncertainties in a long-term time frame [8] or the information available is not enough to model the uncertainties, decision-making theory is a suitable option, which addresses the problem from a decision point of view rather than from an optimization point of view. Yokoyama and Ito proposed an optimal design method for a gas turbine cogeneration system in consideration of uncertain energy demands using the minimax regret criterion [9]. Carpaneto et al. [8] and [10] formulated a comprehensive approach based on decision-making theory for the planning of cogeneration systems with consideration of the large-scale uncertainties in energy demands and energy prices on a long-term time scale. Results showed that the decision-making theory approach is a useful tool that can be easily customized by the decision-makers to define and handle the scenarios to get the satisfactory outcomes. However, alternative plans for the system were specified artificially rather than determined by optimization techniques in their studies. The maximum economic and energy-saving benefits of cogeneration systems may not be achieved. Another common shortcoming of the existing models is that they focus on cogeneration systems without considering cooling technologies, renewable energy technologies, and energy storage technologies.

In the majority of the aforementioned studies, energy demands receive the most significant attention among various types of uncertainties. Large-scale uncertainties in energy demands usually exist because it is difficult to envision the evolution trends of energy demands over a multi-year time frame for DER systems planning [8]. Considering the volatility of energy demands is particularly important and necessary towards the optimal design of DER systems since the main aim of these systems is to meet energy demands and energy supply-demand relationships are key constraints in the optimization model [5].

This paper develops five uncertain programming models for the optimal design of DER systems with consideration of large-scale uncertainties in energy demands. These models are composed of superstructure-based MILP models for the optimal design and operation of the system and five decision-making criteria. The evolution trends of energy demands are described by a set of possible scenarios. With respect to the previous studies, the novelties of the current study mainly lie in three aspects. Firstly, alternative plans for the system are determined by optimization calculation. The MILP models are used to determine the alternative plans and their annual cost under various scenarios. Secondly, the overall framework is developed for trigeneration systems supplying electricity, cooling, and heating demands. Multiple power generation technologies (e.g., gas engines, gas turbines, photovoltaics, and wind turbines) and energy storage technologies (e.g., heat and cold storages) are considered. Finally, the effect of the choice of energy demand scenarios on the decision of installing DER technologies is studied quantitatively for the five methods. For an illustrative example, these methods are applied to a hotel located in Guangzhou, South China. The respective features of these methods are discussed. A sensitivity analysis is conducted by varying the energy demand scenarios.

2. Mathematical formulation

2.1. Mathematical model

The mixed integer linear programming (MILP) mathematical model for the optimal design and the optimal operation of DER system can be found in our earlier publication [11].

2.2. Five uncertainty decision-making criteria

Optimistic criterion is always full of optimism for future development, taking the best condition into account. It identifies the plan with lowest value selected among the minimum annual cost value generated in each scenario as the best plan. Its decision strategy can be expressed as follows [12]:

$$\min_{p\in P}\left\{\min_{s\in S}\left\{C_{Total,p,s}\right\}\right\} \tag{1}$$

$C_{Total,p,s}$ means the annual cost value. It should be noted that the relations applied in the optimistic criterion as well as the following pessimistic criterion, Hurwicz criterion, and Laplace criterion are based on the situation of cost minimization rather than profit or productivity maximization.

Pessimistic criterion is opposite to the optimism decision criterion, assuming the most pessimistic scenario to occur. It identifies the plan with the minimum annual cost value selected among the maximum annual cost values generated in each scenario as the best plan. Its decision strategy can be expressed as follows [12]:

$$\min_{p\in P}\left\{\max_{s\in S}\left\{C_{Total,p,s}\right\}\right\} \tag{2}$$

Hurwicz criterion takes into consideration both the worst and the best possible results, weighted according to the decision-makers' attitude (more optimistic or more pessimistic). It needs to identify an optimism coefficient $\alpha\,(0<\alpha<1)$, which determines the level of the decision-makers' hope to obtain the best possible result. It identifies the plan with the lowest weighted annual cost value in various scenarios as the best plan. Its decision strategy can be expressed as follows [12]:

$$\min_{p\in P}\left\{\alpha\times\min_{s\in S}\left\{C_{Total,p,s}\right\}+\left(1\text{-}\alpha\right)\times\max_{s\in S}\left\{C_{Total,p,s}\right\}\right\} \tag{3}$$

Laplace criterion assumes all scenarios are equally likely. If there are *m* scenarios, the probability of each scenario is 1/*m*. It identifies the plan with the minimum average annual cost value in various scenarios as the best plan. Its decision strategy can be expressed as follows [13]:

$$\min_{p\in P}\left\{\frac{1}{m}\times\sum_{s\in S}C_{Total,p,s}\right\} \tag{4}$$

Minimax regret criterion selects the minimum annual cost value in each scenario as the ideal goal and defines the difference between the other annual cost value and the ideal goal as the regret value. The regret value in each scenario is computed for each plan for all possible scenarios and the maximum regret value is found for each plan. The best plan minimizes the maximum regret value. Its decision strategy can be expressed as follows [14, 15]:

$$\min_{p\in P}\left\{\max_{s\in S}\left\{C_{Total,p,s}-C_{Total,p^*(s),s}\right\}\right\} \tag{5}$$

The modeling and solution of the five uncertain programming models are implemented in Advanced Integrated Multi-dimensional Modeling Software 3.12 (AIMMS 3.12) [16], which is an advanced development environment for modeling and solving large-scale optimization and scheduling-type problems. The MILP models are solved with the CPLEX 12.4 solver.

3. Numerical study

To illustrate the validity and effectiveness of the proposed five uncertain optimization methods and their respective features, a numerical study is carried out on the planning of a DER system for a hotel in Guangzhou, South China. The information of Climate condition, subsidy, electricity and gas tariffs in Guangzhou can be found in [17].

3.1. Energy demands

The hourly electricity, cooling, and heating demands of the hotel on typical days are obtained through field investigation. Over a multi-year time frame for system operation, the possible hourly energy demands are assumed to be a set of seven scenarios from scenario 1 to scenario 7 which are 70%, 80%, 90%, 100%, 110%, 120% and 130% of their values on typical days. This set is used to present the energy demands uncertainty.

3.2. DER equipment options

Table 1 shows the equipment candidates and their technological and economic data as well as the maximum number that can be installed in the hotel. The cut-in, maximum power and cut-out wind speeds of the wind turbine are 3, 15, and 20 m/s, respectively. The area of each photovoltaic panel is 187 m^2. Some specific illustrative examples can be obtained from our earlier publication [17, 18].

Table. 1. Information on the equipment candidates [19-24]

Equipment type	Rated capacity (kW)	Rated efficiency /α/*COP*	Unit capital and installation cost ($/kW)	Unit O&M cost ($/kWh)	Lifetime (year)	Load regulation range	Maximum installed number
Gas turbine	4345	28.3%	880	0.004	15	0.38–1	6
	5200	29.4%	852	0.004	15	0.4–1	6
Gas engine	4500	39.5%	962	0.009	15	0.4–1	6
	5200	40.3%	936	0.009	15	0.4–1	6
Wind turbine	10	1.345	2882	0.0084	25	-	20
Photovoltaic	28	17%	2420	0.0084	25	-	20
Waste-heat boiler	1000	78%	186	0.0027	15	0.38–1	20
	1600	78%	186	0.0027	15	0.3–1	20
Gas boiler	2000	85%	143	0.0027	15	0.3–1	20
	3000	85%	143	0.0027	15	0.3–1	20
Heat storage	-	-	33	0.0013	20	-	-
Absorption chiller	1454	1.417	246	0.001	25	0.05–1.15	20
	2326	1.417	246	0.001	25	0.05–1.15	20
Compression chiller	4220	4.76	146	0.0015	25	0.1–1	20
	5280	5.04	146	0.0015	25	0.1–1	20
Cold storage	-	-	33	0.0013	20	-	-

4. Results and discussions

4.1. Alternative plans

The case described in the previous sections is solved on an Intel® Pentium® CPU G620 (2.60 GHZ) with 4 GB RAM. The optimization design model includes 9650 constraints and 4314 variables (1612 discrete), and its solution time is different at various energy demand scenarios varying from 3 min to 118 h 31 min with an optimality gap of zero. The optimization operation model includes 9612 constraints and 4284 variables (1584 discrete) and can be solved in one second with an optimality gap of zero.

Table 2 shows the optimal numbers and capacities of equipment for the seven alternative plans. The seven plans have the same system structure as shown in fig. 1. The gas engine is selected as the sole power generation facility. Waste-heat boilers and absorption chillers are allocated to recover the exhaust heat generated by the gas engines. Gas boilers and compression chillers are used to supplement the shortages in heating and cooling and act as standby equipment. Heat and cold storages are also allocated. The optimal capacities of gas engines, waste-heat boilers, and absorption chillers increase with increasing energy demands from plan I to plan VII. Gas boilers and compression chillers are allocated with the same capacities in the seven plans, which are determined by the maximum heating and cooling demands. No gas turbine, wind turbine, or photovoltaic is adopted mainly because of the low electricity generating efficiency or the high capital cost of these components.

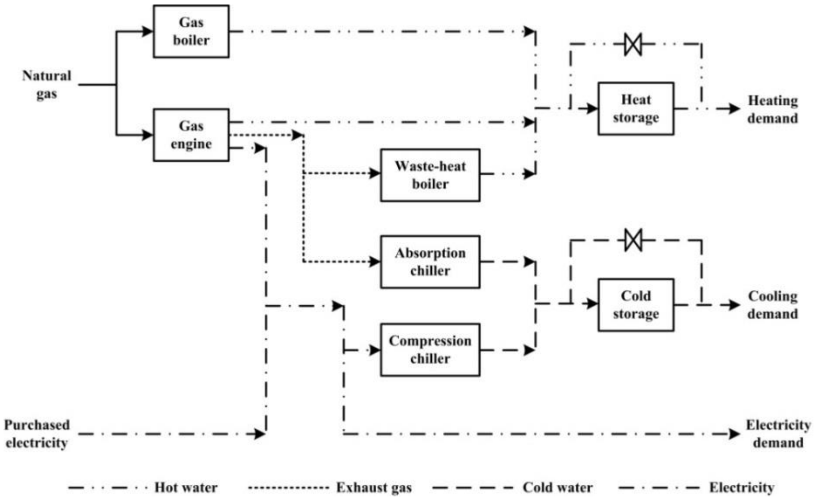


Figure 1. Structure of the DER systems for the seven plans

Figure 2 illustrates the annual cost for each plan under various scenarios. The possible annual cost for the DER system is between 11.64 and 23.01 million dollars. For each plan, the annual cost increases with the increase of energy demands and takes the lowest and highest value at scenario 1 and scenario 7 respectively. For each scenario, the plan corresponding to the filling symbols has the lowest annual cost of all plans because other plans are not large enough, which leading to a higher electricity purchased cost, or too large, which leading to a higher equipment investment cost.

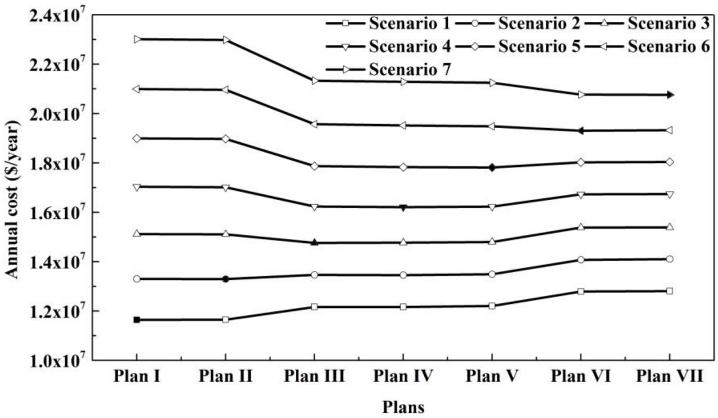


Figure 2. Annual cost for each plan under various scenarios (filling symbols correspond to the lowest annual cost for each scenario)

Table. 2. Optimal numbers and total capacities of equipment for the seven alternative plans

Plan	Based on	Gas engine		Waste-heat boiler		Gas boiler		Absorption chiller		Compression chiller		Heat storage	Cool storage
		Number	Total capacity (kW)	Number	Total capacity (kW)	Number	Total capacity (kW)	Number	Total capacity (kW)	Number	Total capacity (kW)	Total capacity (kWh)	Total capacity (kWh)
I	Scenario 1	2	10,400	3	3000	6	18,000	3	6978	9	47,520	15,133	4185
II	Scenario 2	2	10,400	2	3200	6	18,000	3	6978	9	47,520	17,075	2624
III	Scenario 3	3	15,600	4	4000	9	18,000	7	10,178	9	47,520	13,809	17,726
IV	Scenario 4	3	15,600	4	4000	9	18,000	7	10,178	9	47,520	18,796	4257
V	Scenario 5	3	15,600	3	4800	6	18,000	7	10,178	9	47,520	25,094	4007
VI	Scenario 6	4	20,800	5	5000	6	18,000	9	13,086	9	47,520	21,565	2660
VII	Scenario 7	4	20,800	5	5000	9	18,000	9	13,086	9	47,520	23,825	15,383

4.2. Selection of the best plans

Figure 3 shows the evaluation values for each plan for the five uncertain optimization methods. According to the optimistic method, plan I is chose as the best plan because it has the lowest minimum annual cost. Decision-makers believe that the minimum energy demands (scenario 1) will occur. This decision is risky and requires bearing the risk of the corresponding increase in annual cost because the capacities of gas engines are smaller than the optimal ones when other energy demand scenarios occur, leading to much more amount of electricity purchased cost.

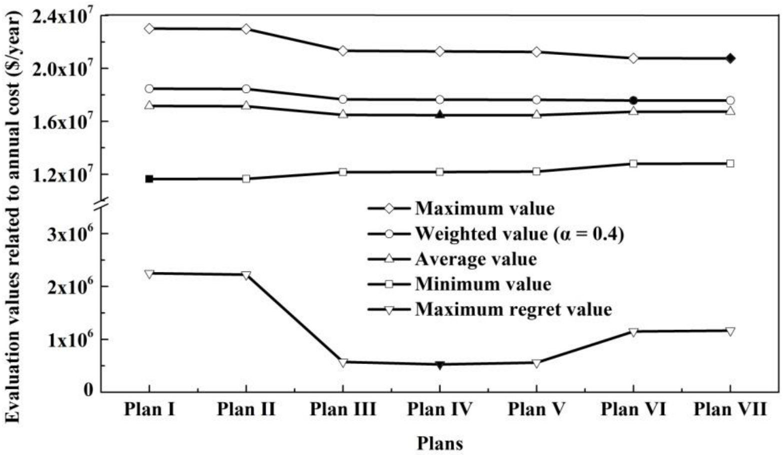


Figure 3. Evaluation values for each plan for the five methods (filling symbols correspond to the best plan)

Pessimistic method provides a reliable but conservative plan for decision-makers, namely plan VII which has the highest initial equipment investment cost. With an extreme pessimistic behavior, decision-makers believe that the maximum energy demands (scenario 7) will occur.

According to the Hurwicz method, if the optimism coefficient α takes 0.4, the best alternative is plan VI because it leads to the lowest weighted annual cost. The key of this method is to determine the optimism coefficient which is with great subjectivity due to being determined by persons. As shown in fig. 4, different choices will be made at different values of α.

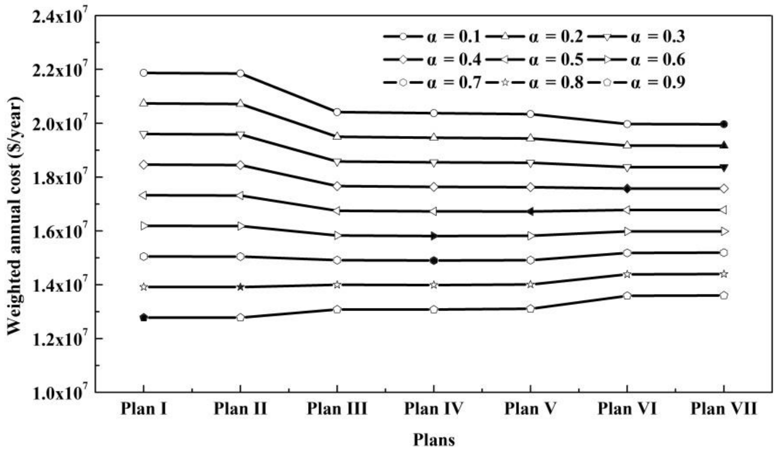


Figure 4. Weighted annual cost for each plan for the Hurwicz method at different values of α (filling symbols correspond to the best plan)

For Laplace method, the best alternative is plan IV with the lowest average annual cost. This method uses all the information in each plan. The key of this method is to judge whether the probability of occurrence of various energy demand scenarios has the same average value.

According to the minimax regret method, plan IV is recommended because it suites the lowest maximum regret in annual cost. There are two possible types of regret for one plan: the system scale is smaller than the optimal one which leads to a higher electricity purchased cost; the system scale is larger than the optimal one which leads to a higher equipment investment cost. The feature of this method is to find a balance point between the two types of regret, namely, find a plan which is robust economically against the uncertainties in energy demands.

It should be noted especially that the five uncertain optimization methods almost lead to different alternative decisions and the best plan depends on the method chosen by the decision-maker who might be optimist or pessimist, or strive to reduce the regret. Each method has a specific utility for a decision-maker or another since different persons mostly have different nature, different perception regarding the probability of the future events, or different attitude towards uncertainty on solving a problem.

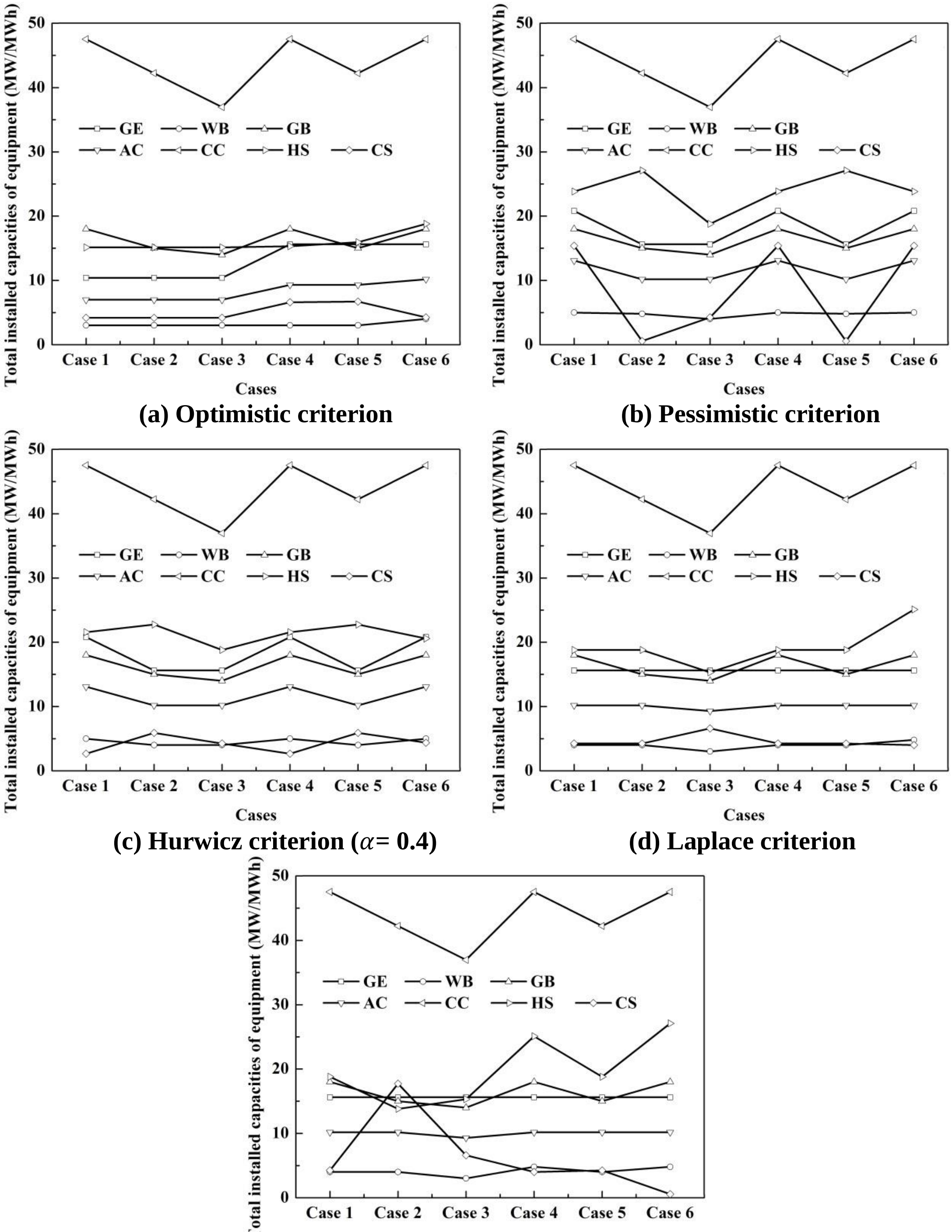
4.3. Sensitivity analyses on scenarios

Sensitivity analyses on energy demand scenarios are performed to understand the level of sensitivity of the scenarios to the decision of installing DER technologies. Six cases are assumed in the analysis. Table 3 shows the ratios of energy demands under various scenarios to its values on typical days for every case.

Table. 3. Ratios of energy demands under various scenarios to its values on typical days for the six cases

		Scenarios						
		1	2	3	4	5	6	7
Cases	1	70%	80%	90%	100%	110%	120%	130%
	2	70%	80%	90%	100%	105%	110%	115%
	3	70%	75%	80%	85%	90%	95%	100%
	4	85%	90%	95%	100%	110%	120%	130%
	5	85%	90%	95%	100%	105%	110%	115%
	6	100%	105%	110%	115%	120%	125%	130%

Figure 5 shows the total installed capacities of equipment for the best plan under various cases for the five methods. It is found that for the five methods, although the best plans under various cases have the same system structure, they have obvious differences in the total installed capacities of equipment. This means that the five methods have high sensitivity to the choice of energy demand scenarios. Therefore, it is very important to predict the evolution trends of energy demands as accurately as possible.



(a) Optimistic criterion **(b) Pessimistic criterion**

(c) Hurwicz criterion (α= 0.4) **(d) Laplace criterion**

(e) Minimax regret method

Figure 5. Total installed capacities of equipment for the best plan under various cases for the five methods

5. Conclusions

In the present paper five uncertain programming models are developed to optimally design a DER system in consideration of large-scale uncertainty of energy demands based on decision-making theory. Superstructure-based MILP models for the optimal design and operation of the system and five uncertainty decision-making criteria (including optimistic criterion, pessimistic criterion, Hurwicz criterion, Laplace criterion, and minimax regret criterion) are integrated. The alternative plans for the system are determined by the MILP models firstly. Then the best plans are identified among the alternatives by using various decision-making criteria.

Application of the proposed optimization models to a hotel in Guangzhou city (China) illustrates the validity and effectiveness of the models. The results indicate that each of the five methods has respective features and utility. Optimistic method is risky and recommends a relative small-scale system. Pessimistic method is reliable but conservative and presents a relative large-scale system. Hurwicz method is with great subjectivity, making different decisions at different values of optimism coefficient. Both Laplace method and minimax regret method identify a moderate-scale system as the best alternative. The former assumes all energy demand scenarios are equally likely, while the latter is strive to minimize the future regret in annual cost. In addition, sensitivity analyses are conducted on the energy demand scenarios. Results show that the evolution trends of energy demands should be predicted as accurately as possible because the five methods have high sensitivity to the choice of scenarios.

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