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A TWO-STAGE MULTI-OBJECTIVE STOCHASTIC PROGRAMMING MODEL FOR DESIGN OF BUILDING INTEGRATED ENERGY SYSTEM

Meng Wang[1], Fangjun He[2], He Liu[3], Pengda Chen[1], Yin Tang[1], Hang Yu[1*]

1 School of Mechanical Engineering, Tongji University, Shanghai, China

2 CNNC Environmental Protection Engineering Co., Ltd, Beijing, China

3 State Grid Tianjin Information & Telecommunication Company, Tianjin, China

ABSTRACT

The integrated energy system is considered to be introduced in buildings, which proposes a new effective approach to improve energy structure in urban areas. The optimal design problem of building integrated energy system is normally presented as mixed-integer nonlinear programming model with deterministic and uncertainty parameters. Moreover, the uncertainty problem results in a more complex problem at a high computational cost. In present work, a two-stage multi-objective stochastic programming model under uncertainty is presented. The proposed model depends on clustering method to create different scenarios in terms of solar radiation, wind speed and energy demand. In addition, the MINLP models of building integrated energy system with stochastic scenarios and deterministic scenarios is investigated to conduct trade-off Pareto optimization with cost-optimal and environment-optimal. The results indicate that the deterministic programming model underestimates the cost and carbon emission of building integrated energy system, while the result of stochastic programming model is closer to the realistic design.

Keywords: renewable energy resources, MINLP, stochastic programming, building integrated energy system, multi-objective optimization

1. INTRODUCTION

The integrated energy system (IES) has recently been considered as an energy-efficient and environmental-friendly way to deal with the urban energy supply problem. The IES usually can be developed in different scales according to various kinds of energy end-users. Meanwhile, the local energy resource including solar or wind can be integrated in IES system to cover the building energy demand with better economic and environmental benefits. Technically, the building integrated energy system (BIES) focuses on the building distributed energy supply problem, which needs more flexibility and accuracy in modeling and optimization. Therefore, the uncertainty modeling and analysis of BIES have been conducted to improve the robustness and reliability of BIES model. In addition, the stochastic programming based on stochastic behavior including hourly, daily and seasonal variation in energy resources and demands can achieve better optimal solution at a higher computational cost.

The optimal design of BIES has been widely investigated in recent years, while the relevant research papers are increasing rapidly. Most of the researchers established the integrated energy system based on MI(N)LP model, in which the commercial solver or heuristic algorithm is introduced to find the optimal solution. Several representative studies concerning IES and uncertainty are as follows. Sharifzadeh et al. [1] established an integrated renewable electricity generation model in GAMS to optimize the power generation considering the uncertainty of wind and solar energies. The results demonstrated that at the price of higher computational costs, stochastic optimization under uncertainty parameters can achieve more realistic and robust solutions for the smart electricity grid design. Mavromatidis et al. [2] proposed a single objective (cost-optimal) stochastic MILP model based on a 10-buildings neighborhood IES system in Swiss, in which energy carrier prices and emission factors, building heating and electricity demands, and incoming solar radiation patterns are considered as uncertainty parameters. The results of comparison with deterministic model illustrated that the deterministic model leads to underestimation of the system costs and the renewable energy capacity. Li et al. [3] proposed a two-stage approach combining multi-objective optimization with decision-making for CCHP dispatch problem. Kang et al. [4] conducted a robust optimal framework of IES system based on life-cycle performance analysis using a probabilistic approach. The proposed model enables robust optimal design with economic benefits and higher total system energy efficiency in the latter years of its life-cycle.

In view of higher complexity caused by the uncertainty issue, researches proposed some valid methods based on statistics analysis or heuristic solutions. Pfenninger [5] analyzed many clustering methods to find out the optimum time resolution for IES design. The results illustrated that the time resolution is so highly dependent on case study that no conclusion of optimum resolution can be drawn. Sarshar et al. [6] used the artificial neural network (ANN) and wavelet decomposition approach to forecast wind power over various time horizon and reduce uncertainty. Niu et al. [7] conducted a robust optimization model of BIES under cooling load uncertainty by means of Monte Carlo simulation. The case study of a hospital in Tianjin demonstrated the effectiveness and accuracy of the proposed model.

In general, the design of BIES under uncertainty is a relatively complex task, which needs to deal with non-linear problem and several uncertainty parameters with high time resolution. Meanwhile, the computational capability needed by stochastic multi-objective optimization model should be acceptable in common computing platforms. Therefore, this study aims to explore a stochastic multi-objective optimization framework of BIES under uncertainty. Based on the hourly meteorological data of solar radiation and wind speed, and energy demands simulated by DeST (A simulation tool in building energy-consumption), several probabilistic uncertainty scenarios are generated by K-mediods (a typical clustering algorithm) in order to accurately represent the characteristics of above uncertainty parameters and significantly reduce the computational cost. Meanwhile, a MINLP optimal design and dispatch model of CCHP system is established in GAMS, while some operation constraints including part-load ratio, on/off limits, and start-limits are introduced in the present model to make it closer to practical design. The eps-constraint method is implemented to obtain Pareto frontier with multi-objective optimization (economic and environmental objective). Finally, the comparison of the optimal results between stochastic and deterministic model for BIES system is analyzed.

2. METHODOLOGY

2.1 Two-stage Stochastic Programming and Objectives

The two-stage stochastic programming is a typical stochastic optimization method which is widely-used in transportation modeling and supply chain planning. In this method, the decision variables of BIES model have been divided into two groups including first stage (capacity) and second stage (operation), which can be described as follows:

$$\begin{aligned} \text{Prime:}\ & \min f(x,y)+\sum g(x,y,\xi) \\ & \text{s.t. } \varphi(x,y)=0 \\ & \psi(x,y)\le 0 \\ & x\in R^{+}, y\in\{0,1\} \end{aligned} \tag{1}$$

$$\begin{aligned} \text{Sub:}\ & g(x,y,\xi)=\min_{\lambda} g(x,y,\xi,\lambda) \\ & \text{s.t. } \varphi(x,y,\xi,\lambda)=0 \\ & \psi(x,y,\xi,\lambda)\le 0 \\ & \lambda\in R^{+} \end{aligned} \tag{2}$$

The two-stage stochastic optimization Eq. (1,2) can be further converted into a more simple and clear formulation with probability parameters in Eq. (3):

$$\min f(x,y)+\sum\left(\theta_s\cdot g_s(x,y,\xi_d)\right) \tag{3}$$

where θ_s is the probability of each scenario.

In the proposed model, the annual total cost and annual carbon emission are chosen as two objective functions to characterize the economic-environmental performance of BIES model. The annual total cost (ATC) is one of the most frequently utilized objectives in BIES, which includes the capital cost, the fuel cost, the maintenance cost, and grid electricity purchasing cost and electricity feed-in revenue, as shown in Eq. (4):

$$
\begin{aligned}
ATC &= \sum_t CAP_t \times C^{\mathrm{CAP}} \times CRF_t + \sum_s OPEX_s \times prob_s \\
OPEX_s &= \sum_h Q^{\mathrm{ele}}_{\mathrm{chp},s,h} \times C_{\mathrm{NG}} + Q^{\mathrm{heat}}_{\mathrm{b},s,h} \times C_{\mathrm{NG}} + \\
&\qquad Q^{\mathrm{ele,heat,cool}}_{t,s,h} \times C^{\mathrm{maint}}_t + Q_{\mathrm{im},s,h} \times C_{\mathrm{im}} - \\
&\qquad Q_{\mathrm{ex},s,h} \times C_{\mathrm{ex}}
\end{aligned}
\tag{4}
$$

where *CRF* is the capital recovery factor, which can be calculated by interest rate and project life. The subscript *t* and *h* denote the selected technologies and hours. The symbol *s* denotes the scenarios generated in section 2.3.

The environmental objective is another key factor for developing integrated energy systems. In this model, the annual carbon emissions (ACE) is considered as the environmental objective as defined in Eq. (5).

$$
\begin{aligned}
ACE &= \sum_s DLY_s \times prob_s \\
DLY_s &= \partial_{\mathrm{NG}} \times \sum_h \left(Q^{\mathrm{ele}}_{\mathrm{chp},s,h} + Q^{\mathrm{heat}}_{\mathrm{b},s,h} \right) + \partial_{\mathrm{grid}} \times \sum_h Q_{\mathrm{im},s,h}
\end{aligned}
\tag{5}
$$

where ∂_{NG} and ∂_{grid} are the emission factors of natural gas and the grid, respectively. The *prob* is the abbreviation of probability.

2.2 Model description

An illustrative renewable assisted BIES optimization model is proposed as shown in Fig. 1. The CHP (Internal Combustion Engine) is fueled by natural gas, and the generated power is integrated with solar PV power, wind turbine power, less the potential consumption of the electrical chiller (EC) and the air source heat pump (ASHP). Interaction with the grid is also enabled considering the intermittence of solar and wind power. Meanwhile, the heat along with the power generation of the CHP is utilized for heating supply by merging the heating flow with the boiler and the ASHP, less the potential consumption of absorption chiller, and a heating storage tank is considered.

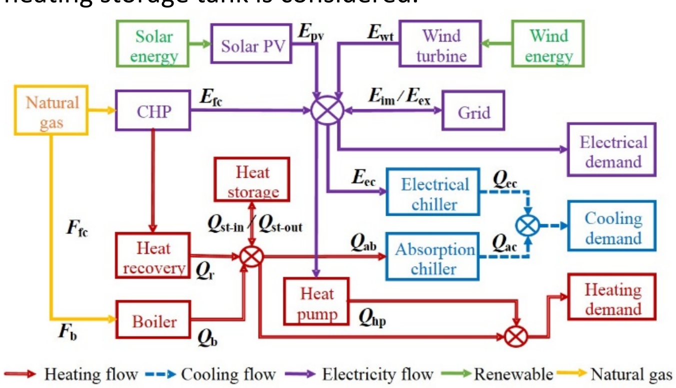

Fig. 1 Renewable assisted CCHP-based BIES layout

Electrical, heating and cooling balances are established in accordance with the system layout as illustrated in Fig. 1. The electrical demand is fulfilled by the solar PV panel, the wind turbine, the internal combustion engine, the imported electricity from the grid, minus the possible consumption by the electrical chiller and the heat pump or export to grid as shown in Eq. (6). Meanwhile, the heating demand is satisfied by the recovered heat from the internal combustion engine, the gas boiler, the air source heat pump (ASHP), considering interaction with the heat storage tank, minus the possible heat consumption by the absorption chiller as presented in Eq. (7). In addition, Eq. (8) illustrates the cooling balance, where the cooling demand is fulfilled by the electrical chiller and the absorption chiller.

Electrical balance:

$$
\begin{aligned}
Q^{\mathrm{ele}}_{\mathrm{demand},s,h} &= Q^{\mathrm{ele}}_{\mathrm{wt},s,h} + Q^{\mathrm{ele}}_{\mathrm{pv},s,h} + Q_{\mathrm{im},s,h} + Q^{\mathrm{ele}}_{\mathrm{chp},s,h} \\
&\quad - Q_{\mathrm{ex},s,h} - Q^{\mathrm{ele}}_{\mathrm{ec},s,h} - Q^{\mathrm{ele}}_{\mathrm{hp},s,h} \quad \forall s,h
\end{aligned}
\tag{6}
$$

Heating balance:

$$
\begin{aligned}
Q^{\mathrm{heat}}_{\mathrm{demand},s,h} &= Q^{\mathrm{heat}}_{\mathrm{re},s,h} + Q^{\mathrm{heat}}_{\mathrm{b},s,h} - Q^{\mathrm{heat}}_{\mathrm{st\text{-}in},s,h} + Q^{\mathrm{heat}}_{\mathrm{st\text{-}out},s,h} \\
&\quad + Q^{\mathrm{heat}}_{\mathrm{hp},s,h} - Q^{\mathrm{heat}}_{\mathrm{ac},s,h} \quad \forall s,h
\end{aligned}
\tag{7}
$$

Cooling balance:

$$
Q^{\mathrm{cool}}_{\mathrm{demand},s,h} = Q^{\mathrm{cool}}_{\mathrm{ac},s,h} + Q^{\mathrm{cool}}_{\mathrm{ec},s,h} \quad \forall s,h \tag{8}
$$

where s denotes the scenario, h means the hour, which is the time step of the proposed model. The mathematical formulations of each component are presented in Refs. [8-10]

2.3 Scenario generation

In present study, the uncertainties in solar radiation intensity, wind speed, electric demand, heat demand, and cool demand profiles are captured by generating representative scenarios as shown in Fig. 2. As the unit of electric demand, heat demand, and cool demand is kWh, the accumulated value of different kinds of hourly energy demand has been characterized as one bifurcation point to split into two groups (high energy-demand cluster and low energy-demand cluster). Therefore, three-layer classification including solar radiation intensity, wind speed and energy demand is considered to generate stochastic scenario, in which each layer classification consists of binary clustering by means of K-mediods. Before this, all data have been manually classified into three groups by summer, winter and transition season. Meanwhile, three other scenarios have been generated to represent the maximum electric demand, heat demand and cool demand, respectively. The cluster probability is calculated as the ratio of the number of observations assigned to the cluster and the total number of observations.

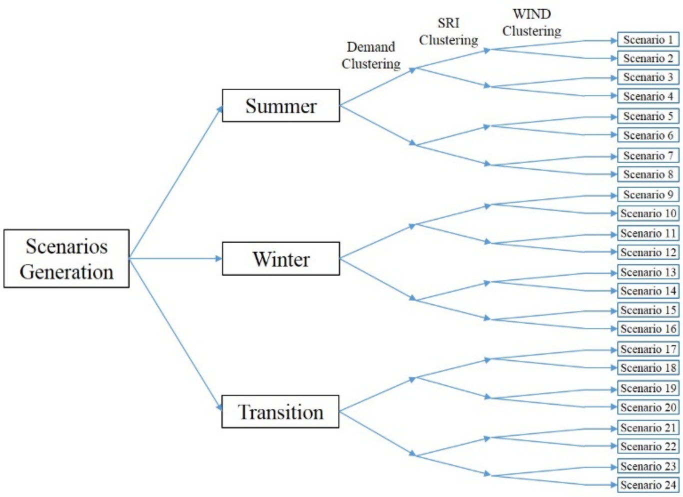

Fig. 2 Scenario construction of stochastic scenarios.

2.4 Computing platform

For the purpose of comparing and considering the practicability, all modelling and optimization are conducted on the same computer system, which is an ordinary PC with Intel Xeon E3 3.20 GHz and 24 GB RAM. The modelling software is GAMS by calling the LINDO solver. The length of the planning horizon is 10 years assuming the demand and price are stable during this period, and the temporal resolution is 1h. The optimality setting is 0.1% and other settings remain as default.

3. CASE STUDY

To compare stochastic programming approach with deterministic programming approach, a case study is conducted by implementing the illustrative building integrated energy system (BIES) to an all-day operational hotel in Beijing in "cold" climate zone of China.

The uncertainty parameters in this study consist of solar radian intensity (SRI), wind speed (WS), and energy demand including electricity, heat and cool. The hourly meteorological data can be obtained from National Meteorological Information Center, while the energy demand with hourly resolution is modelled by a building performance simulation software named "Designer`s Simulation Toolkit (DeST)". To present the data of uncertainty parameters more clearly, the data only for one year has been shown in Fig. 3 and Fig. 5. Moreover, Fig. 4 illustrates the time-of-use energy prices and energy demand, while the solar radiation intensity and the wind speed are presented in Fig.3.

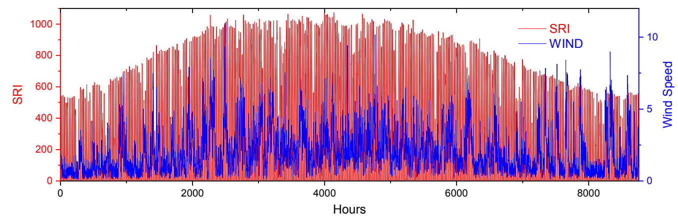

Fig. 3 Hourly data of SRI and wind speed in one year

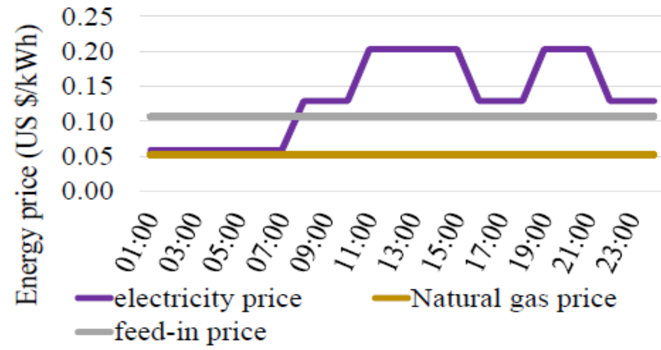

Fig. 4 Time-of-use energy prices

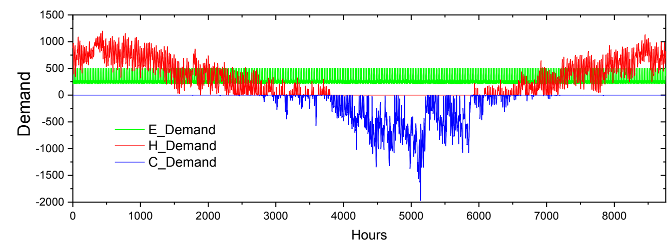

Fig. 5 Hourly data of energy demand in one year

The details of state-of-the-art technical, economic and environmental input parameters are presented in Ref. [11], which include internal combustion engine, wind turbine, solar PV, boiler, electrical chiller, absorption chiller, heat pump, heat exchanger and the heat storage tank.

As mentioned above, several scenarios have been generated in two-stage stochastic programming model. Meanwhile, the deterministic model has been established for comparison with the stochastic model. In the deterministic model, the five uncertainty parameters have been hourly averaged to construct the typical days for each season.

4. RESULTS AND DISCUSSION

4.1 Multi-objective optimization results

The Pareto frontier determined by the ε-constraint method is depicted in Fig. 6. The point labeled A in this figure shows the result of single-objective optimization for stochastic model with the lowest ATC and the highest ACE, while A' is for deterministic model. Point B indicates the minimum ACE of this stochastic BIES model with the worst ATC, while B' is for deterministic model. It is the equivalent of a single-objective optimization of objective 1. All of the points in-between represent the minimization of objective 2 with progressively more stringent constraints on objective 1, to make it increase.

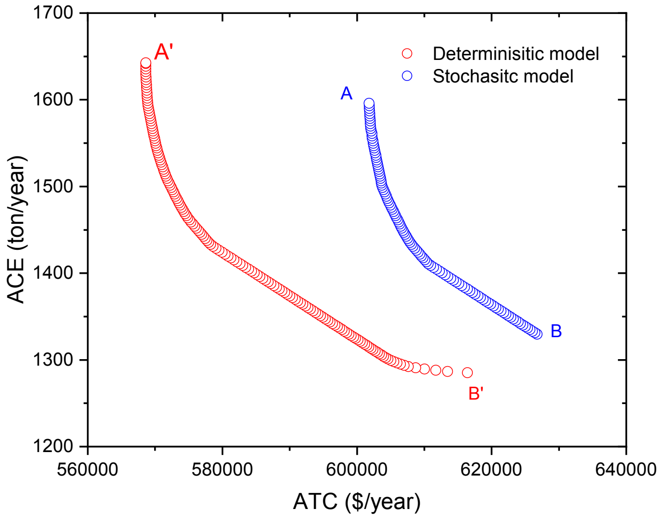

Fig. 6 Pareto frontier for deterministic and stochastic programming model

It is obvious that improving the ATC value is at the cost of increasing the ACE. The trends of Pareto frontier for stochastic and deterministic programming are quite similar. However, it can be observed that the Pareto frontier of deterministic model is nearer to the ideal point (cannot be achieved) than that of stochastic model. The ACE value of non-dominated solutions in Pareto frontier of deterministic programming is in the range of 1285-1642 (ton/year), while the ATC value is from 568000 to 616000 ($/year). In the Pareto frontier of stochastic model, the range of optimal ATC is 600000-626000 ($/year), while the ACE is in the range of 1350-1600 (ton/year).

4.2 Discussion

By comparison with deterministic programming, the stochastic programming model has much more constraints caused by several scenarios, which may result in great computation consumption. Therefore, there must be a trade-off between scenario number and computation cost, especially when some component models are non-linear such as PV, Wind turbine or off-design model, in which polynomial or trigonometric function may exist. The conflict between accuracy and computing cost is still difficult to solve.

In this case study, the Pareto frontier of stochastic programming is higher (worse) than that of deterministic programming. The reason is that the deterministic programming neglects the effect of maximum energy demand, even though it is relatively rare, which may underestimate the cost and carbon emission of BIES system. However, in the stochastic model, the maximum energy demand scenario with small probability has been converted to various constraints in the optimization process, which may constrain the capacity of each energy-supply component to a relatively high value range. In other words, the stochastic scenarios produce some lower bounds for the decision variables of capacity in the first stage. Meanwhile, it can be found that the Pareto frontier's ranges of the both objective function values for stochastic programming are smaller than those for deterministic programming. The reason is that, with the increase of stochastic scenario number, the constraints of model become stronger and more complicated, contributing to a decreased amount of feasible solutions. Therefore, the gap between the upper and lower bound of the objective function value as well as their search spaces have been reduced in the stochastic programming.

5. CONCLUSION

In this paper, a two-stage stochastic programming model (MINLP) has been established to optimize the design and operation of the renewable assisted CCHP-based BIES system, which has been implemented on the case study of a hotel in Beijing of China. The decision variables have been split into two groups including capacity setting and dispatch operation. Before optimization, the scenario generation using clustering method in hourly resolution has been conducted to create several stochastic scenarios to capture the characteristics of uncertainty parameters including solar radiation intensity, wind speed, electric demand, heating demand and cooling demand. Moreover, the economic-environmental multi-objective optimization has been addressed to obtain the Pareto frontier by means of eps-constraint approach. Finally, the comparison between the optimization results of deterministic and stochastic programming has been conducted and analyzed. The major conclusions that have been drawn are as follows:

(1) The proposed stochastic programming model enables the multi-objective optimization of design and operation for the BIES system. In addition, the optimal Pareto frontier can be obtained by integration of the proposed stochastic programming model with the eps-constraint method.
(2) The clustering method can capture the characteristics of several uncertainty parameters through generating various stochastic scenarios. With the increasing number of stochastic scenarios,

the computational cost rises rapidly, which is needed to be controlled at acceptable levels.

(3) The comparison between the deterministic and stochastic programming model illustrates that the deterministic programming model underestimates the cost and carbon emission of BIES system. The proposed stochastic programming model can take into account various uncertainty in order that the optimization results become more realistic and practicable.

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