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Power Generation Investment Portfolio Optimization under Output and Price Uncertainties#

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ABSTRACT

For power generation compony, decisions are made rely on regulation, policy, capacity factor and company's financial situation. The coupled use of multiple energy sources can take advantage of the complementarity of multiple energy sources to improve energy efficiency. However, the increasing number of renewables and multi-energy loads entering the energy system increases the multiple uncertainties of energy system. These decision models must capture the challenge induced by the penetration of renewable energy (RE) and the role of energy storage. In this paper, we establish a two-stage stochastic optimization model and apply Latin hypercube sampling (LHS) to dealing with correlated random variables and study the investment portfolio among conventional power generators and renewable energy with different levels of volatility. Then, multi-dimensional correlation scenario set are generated to confirm the applicability of the model. The results shown that the volatility of renewable energy increases the proportion of flexible scheduling units in the system as well as the system cost in investment and operation. Energy storage capacity is being used to address intermittence of RE to make power system stable.

Keywords: renewable energy resources, expansion stochastic planning, capacity investment, uncertainty, representative day selection

NONMENCLATURE

Abbreviations	
RE	Renewable energy
LHS	Latin hypercube sampling
ESS	Energy storage system
RPS	Renewables portfolio standards
Indices	
s	Index for scenarios
te	Index for generation technologies
p	Index for power plants/locations
t	Index for time periods
Parameters	
T	*Total time periods*
ic_{te}	Investment cost per unit capacity
r	Discount rate
lt_{te}	Lifetime of technology
omc_{te}	Fixed operation and maintenance cost per unit power capacity
$ep_{te,p}$	Installed capacity
vc_{te}	Variable cost per unit power
$fp_{te,t}$	Fuel price per unit
fc_{te}	Fuel consumption for per unit electricity generation
$C_{NRE,p}^{start}$	Startup cost
$D_{s,t}$	Load
μ_L	Capacity reserve coefficient
$\overline{ramp}_p^{NRE}$	Ramp up/down limit
$\underline{g}_p^{NRE}$	Minimum stable level of a unit
$\overline{g}_p^{NRE}$	Maximum capacity of a unit
$\bar{g}_{s,j,t}^{RE}$	Maximum power output of RE
λ	Penetration rate of renewable energy
$Ratio^{char-gen}$	Discharge efficiency of battery
$\overline{g}_p^{battery}$	Maximum discharge power
Variables	
$nc_{te,p}$	Newly investment capacity
$z_{te,p}$	Binary investment or not decision
$g_{s,te,p,t}$	Power output
$g_{s,te,p,t}^{CURT}$	Power curtailment
$o_{s,p,t}^{NRE}$	Number of operating units
$g_{s,p,t}^{CHARGE}$	Energy stored of battery storage system
$es_{s,p,t}$	Energy storage level

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1. INTRODUCTION

It is crucial to promote and optimize the power generation energy mix to implement effective carbon reduction strategies. A significant proportion of renewable energy power output in the electricity system decreases reliance on fossil fuels and carbon dioxide emissions while also diminishing operational expenses. Although there are many advantages of renewable distributed generation, the intermittent supply of non-dispatchable wind and solar photovoltaic power creates uncertainties in the planning and operation of microgrids [1,2]. These uncertainties, as well as load variations, can lead to operational and control problems [3].

The uncertainty of power system can be categorized into short-term and long-term uncertainty [4,5]. Long-term uncertainties include capital expenditures, policy incentive programs, and fuel prices. Short-term uncertainties are more related to operational parameters, such as hourly load fluctuations, hourly renewable resource availability, and transmission line and generation system failures [6,7]. In addition, the operation of energy storage systems facilitates the integration of renewable energy by mitigating fluctuations or minimizing local net loads and renewable energy cuts, which plays an important role in addressing uncertainty and reducing carbon emissions [8,9]. Simultaneously, the volatility of energy prices should be considered [10]. Electricity prices in the Texas power market between 2018 and 2023 have significant monthly seasonality and a steady upward trend, while natural gas prices have no clear pattern but are more volatile. Although the uncertainty of price does not affect the feasibility of decision-making, the accurate prediction of price parameters can improve the profitability of thermal generating units [11]. Future savings from replacing conventional technologies with renewable ones, such as replacing electricity purchased from the grid with rooftop solar systems, should take these price changes into account.

In order to deal with uncertainty, various methods have been used in the existing literature [3,8,12–14], such as stochastic optimization, robust optimization, Monte Carlo simulation, Latin mixed cubic sampling technique, heuristic moment matching (HMM) method Taguchi's orthogonal array testing, and probabilistic statistical methods. In addition, some literature has modelled uncertainties of the wind and PV generation while ignoring the correlation with price uncertainty.

Decision makers such as energy companies face an important problem: how to make decisions about the direction of the power system to meet these challenges without understanding the scope of the challenges or the costs and benefits of potential future technologies [15,16]. The operational strategies of power generation system differ from one application to another. Therefore, appropriate generator technologies, the optimal capacity and location selection, and the optimal operation strategy, including charging and discharging cycles, need to be chosen carefully so as to result in the maximum benefit to the power company. To make these decisions, we turn to using models (simplified representations of systems) to predict and evaluate different future investment portfolio options. Our model is to make strategic investment decisions based on the operational level data granularity for renewable energy yield and energy demand at a fine level.

This paper is organized as follows: Section 2 presents the proposed model. Section 3 covers the results and discussions, while Section 4 summarizes the main findings of the paper.

2. METHODOLOGY

2.1 Model structure

This section introduces our model and assumptions. We consider an electricity supplier that is responsible for meeting the random market demand.

This problem is formulated as a stochastic program which optimizes the total cost consisting of the investment costs, generation costs with resources based on the above practice. The model includes thermal-generating power plants with three types of technology, NGCT, WIND, PV, namely. The model consists of two stages. On the strategic level, we focus on particular technology investment in particular locations and the optimal capacity, on the operational level, we consider multiperiod production planning and scheduling decisions.

2.2 Objective function

The model aims to minimize the annualized system total cost. Specifically, this function consists of the cost of electricity investments, operations and maintenance (O&M), and production in electricity generating facilities, and investments cost in storage facilities, and the start-up cost of dispatchable power generator over the whole period of time from $t = 1$ to $t = T$. The factor $8760/T$ computes the length of the optimization period in years to adjust the computed total cost of electricity to yearly total cost.

$$\min \sum_{te} ic_{te} \frac{(1+r)^{lt_{te}}}{(1+r)^{lt_{te}-1}} \cdot \sum_{p} nc_{te,p} \cdot z_{te,p} +$$
$$\frac{8760}{T} \sum_{te} omc_{te} \sum_{p} \left(nc_{te,p} \cdot z_{te,p} + ep_{te,p}\right) +$$

$$\frac{8760}{T}\sum_s prob_s\left(\sum_{te}\sum_p\sum_t vc_{te}\cdot g_{s,te,p,t}+\sum_{te}\sum_p\sum_t fp_t\cdot g_{s,te,p,t}\cdot fc_{te}+\sum_{NRE}\sum_p\sum_t sc_{s,p,t}^{NRE}\right) \quad (1)$$

2.3 System conditions

2.3.1 Load balance constraint

For each time step and scenario, the summation of generators' gross output and load loss equals the total demand.

$$\sum_{te}\sum_p\left(g_{s,te,p,t}-g_{s,te,p,t}^{CURT}\right)-g_{s,p,t}^{CHARGE}=D_{s,t} \quad (2)$$

2.3.2 Spinning reserves constraint

The installed capacity in the planning should include a portion as load reserve, which is generally provided by flexible gas-fired units and energy storage system. Therefore, the following constraints should be met in Eq. (3):

$$\sum_{NDTE}\sum_p g_{s,p,t}^{NDTE}-\sum_{te} g_{s,te,p,t}^{CURT}+\sum_{DTE}\bar{g}_{s,p,t}^{DTE} \geq D^{peak}\cdot(1+\mu_L) \quad (3)$$

2.4 Power plant operation constraints

2.4.1 Thermal power unit climbing constraints

Period (hourly) ramping constraints that ensure that sufficient flexible capacity is committed to meet challenges created by variable renewable technologies.

$$\left|g_{s,p,t+1}^{NRE}-g_{s,p,t}^{NRE}\right| \leq \overline{ramp}_p^{NRE}, NRE\in\{NGCT\} \quad (4)$$

Eq. (5) ensures a start cost must be paid when a unit started. And Eq. (6) constraints the thermal power generators service to the maximum capacity over minimum stable operating level of the unit.

$$sc_{s,p,t}^{NRE} \geq C_{NRE,p}^{start}\cdot\Delta o_{s,p,t}^{NRE}, NRE\in\{NGCT\} \quad (5)$$

$$u_{NRE,t}\cdot \underline{g}_p^{NRE} \leq g_{s,P,t}^{NRE} \leq u_{NRE,t}\cdot \overline{g}_p^{NRE}, NRE\in\{NGCT\} \quad (6)$$

2.4.2 Renewable power output constraints

The actual power output of each technology is non-negative and should not exceed the generating capacity of the corresponding technology. However, the power generated from these renewable sources depends on climatic factors such as wind speed, solar radiation, temperature, etc., which leads to uncertainties and poses new challenges to planning issues. The nonlinear relationship between wind speed, solar irradiance and power output as shown in Eq. (7) and (8).

$$\bar{g}_{WIND,t}=\begin{cases}0, & 0<v_t\leq v_{in}\\ \frac{v_t-v_{in}}{v_{rated}-v_{in}}\cdot g_R, & v_{in}<v_t\leq v_{rated}\\ g_R, & v_{rated}<v_t\leq v_{out}\\ 0, & v_t>v_{out}\end{cases} \quad (7)$$

$$\bar{g}_{PV,t}=\eta_{PV}\cdot S_{PV}\cdot\theta_t \quad (8)$$

The renewable power generation is determined by the capacity factor associated with the representative period, and curtailment can reduce renewable generation.

$$0\leq g_{s,p,t}^{RE}\leq \bar{g}_{s,p,t}^{RE}, RE\in\{WIND,PV\} \quad (9)$$

$$g_{s,RE,p,t}^{CURT}\geq 0, RE\in\{WIND,PV\} \quad (10)$$

At each planning stage, it is assumed that the lower limit of available units for wind and PV farms is a certain percentage of the total load demand energy. The following percentage shown in Eq. (11) is chosen based on the RPS policy.

$$\sum_{RE} g_{s,i,t}^{RE}\geq\lambda\cdot\sum_{te} g_{s,i,t}^{te}, RE\in\{WIND,PV\} \quad (11)$$

2.5 Battery energy storage system

Maintaining grid stability is becoming increasingly complex with the growing demand and penetration of renewable energy sources in the electricity mix, hence the need for grid-scale large-scale energy storage systems, and we have chosen lithium-ion batteries as a model for energy storage systems. Energy storage system (ESS) could power energy during the valley load period and provide power output during the peak load period, which could provide reserve services.

Eqs. (12) and (13) limit the level of energy stored at any given time. Eqs. (14), (15) and (16) limit the charge rate and discharge rate of the energy storage system, respectively.

$$es_{s,p,t-1}+g_{s,p,t}^{CHARGE}\cdot\Delta t-g_{s,p,t}^{DISCHARGE}\cdot\Delta t=es_{s,p,t} \quad (12)$$

$$0\leq es_{s,p,t}\leq nc_{te,p}\cdot z_{te,p}, \forall te\in\{battery\}, t\in T \quad (13)$$

$$0\leq g_{s,p,t}^{CHARGE}\leq Ratio^{char-gen}\cdot nc_{te,p}\cdot z_{te,p} \quad \forall te\in\{battery\}, t\in T \quad (14)$$

$$0\leq g_{s,p,t}^{DISCHARGE}\cdot\Delta t\leq es_{s,p,t-1} \quad (15)$$

$$0\leq g_{s,p,t}^{DISCHARGE}\leq \overline{g}_p^{battery} \quad (16)$$

2.6 Modelling of uncertainty matrix

Latin hypercube sampling (LHS) is a multidimensional stratified sampling method. It aims to improve accuracy by generating more evenly distributed samples. The distribution of random variables is divided into intervals of equal probability, and a sample point is randomly selected in each interval [17,18]. The goal of sampling is to produce a representative sample that adequately reflects the distribution of the random input data, while the goal of rearrangement is to adjust the correlation of all these random input data samples to the acceptable level. The sampling and arrangement details are as follows.

Let $X_1, X_2, \dots, X_K$ be the K dimensions input random variables in a probabilistic problem, then the cumulative distribution function of can be expressed as follows:

$$Y_k=F_k(X_k), k=1,2,\dots,K \quad (17)$$

First, the interval $[0,1]$ is divided into N non-overlapping subintervals of equal length, where N is the number of samples. Second, one value is randomly selected from each subinterval. The sampled values of X_k are determined by

$$x_{kn} = F_k^{-1}\left(\frac{n-rand}{N}\right), k \in K, n \in N \tag{18}$$

where $F_k^{-1}(\cdot)$ is the inverse function of $F_k(\cdot)$.

The sampled values of X_k are set as a vector, $[x_{k1}, x_{k2}, \dots, x_{kN}]$. When the samplings of all of the K input random variables are done, an initial sampling matrix S with a dimension of $K \times N$ can be obtained.

$$S = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{K1} & x_{K2} & \cdots & x_{KN} \end{bmatrix} \tag{19}$$

Rearrange the elements of each row of the matrix to simulate the random combination of uncertainty parameters as follows. Cholesky decomposition is proposed and adopted in LHS to ensure minimal correlation between matrix rows because its computational burden is the least compared with the above methods apart from random permutation. The performance of LHS can also be further improved.

During the rearrangement process, a sorted matrix L is generated to indicate the rank of the arrangement of the main sample matrix S. Each row of S are then rearranged according to the rank number of its corresponding row of L to reduce correlation. Correlations can be represented by a $K \times K$ correlation matrix ρ. The root-mean-square correlation ρ_{rms} of ρ is calculated here to evaluate the correlation and can be expressed as follows:

$$\rho_{rms}^2 = \frac{\sum_{j=2}^{K}\sum_{k=1}^{j-1}\rho_{kj}^2}{\frac{(N-1)N}{2}} \tag{20}$$

where ρ_{kj} is the off-diagonal elements in correlation matrix ρ.

$$\rho_L = DD^T \tag{21}$$

where D is a lower triangular matrix. Then a $K \times N$ matrix G can be constructed by the following formula:

$$G = D^{-1}L \tag{22}$$

Since G has an identity correlation matrix, that is, the vector formed by the row is independent, the updated L, that is, the rank of the data in the row, has a smaller correlation.

3. RESULTS

In this paper, the sampling is based on the historical hourly electricity load, wind and solar power generation projection data of three specific locations. Twelve representative days were identified based on Section 2.6, and various penetration rate targets for renewable energy were evaluated. To evaluate the impact of uncertainty, we imposed additional limits on the selection of potential sites.

3.1 Investment decisions and cost analysis

It is noted from Fig. 1, renewable energy capacities are affected by expected output and volatility, while traditional energy capacities are affected by RPS target. The stochastic optimal solution is obtained by considering multiple scenarios of possible inputs, so the decision is more robust and close to the actual expectations of the actual situation. Therefore, for all practical purposes, the stochastic optimal result is more realistic, unless the deterministic case input is a very accurate prediction and has little deviation from the predicted input in real life. It can be seen that in stochastic case, traditional energy power has received more investment in low RPS target scenario, while solar photovoltaic power generation with greater uncertainty has almost no investment in stochastic case, which is because renewable energy power has different output and probabilities, in order to meet the system constraints at a lower cost, thermal power generation is needed as backup. Wind energy receives investment under any circumstances, but the location and capacity of its construction vary according to RPS targets. When RPS targets are relatively low, only the wind power projects in Wildorado and Roscoe obtain investment, because both locations have higher expected wind energy output. The investment in energy storage systems shows a contrasting situation compared to gas-fired power generation.

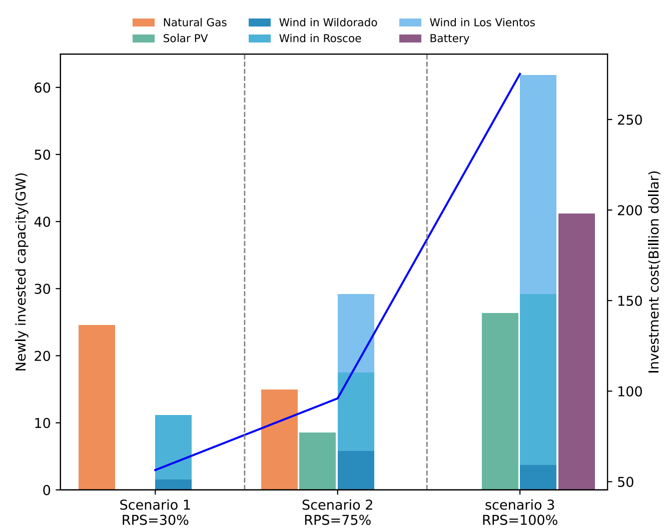

Fig. 1 Newly invested capacity by sources under different uncertainty scenarios

The blue line indicates that the investment costs of the system vary with the RPS targets in Fig. 1. The expected cost in stochastic scenario is also greater than in the deterministic case because there are scenarios with high loads and low RE capacity factor. The cost difference is mainly reflected in the investment cost and operation and maintenance cost, which is consistent with the investment situation mentioned in background, and because renewable energy does not require fuel consumption, and the price of natural gas fuel is not high, the fuel cost difference in the two cases is not significant. The increase in the RPS target will increase the investment cost of the system.

3.2 Dispatch result

The power output by sources under different RPS scenarios, as shown in Fig. 2. When the output uncertainty of renewable energy is contained in our model, the thermal power unit needs to be started and shut down frequently to adapt the balance of grid. Energy storage system ensures efficient peak shaving. In the scenario of higher renewable energy penetration, the charge and discharge energy of the energy storage system is greater, because the energy storage bears the reduced and supplement peak load capacity of the thermal power unit. At night, because the demand is at lower level and the wind output is higher, the wind power generators can meet the load demand by themself. Due to the low levelized cost of electricity of wind power, under the goal of minimizing the total cost of system, when the wind power output is too high during the daytime, there will occur solar power curtailment. The power output is subject to the results of the energy investment in the Section 3.1. Higher RPS targets lead to higher curtailment of wind and solar power.

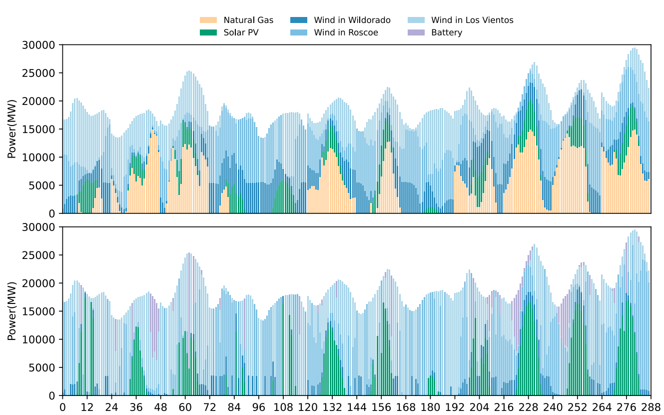

Fig. 2 Hourly power output by sources

4. CONCLUSIONS

Based on the methodology of the characteristic day acquisition and sampling, this study developed a multi-energy investment and dispatching model that takes both economic and renewable development goals. This model has been applied to several different scenarios to evaluate their decision level, and responding uncertainty increases the overall cost of the system as well as production balancing pressures.

The utilization of the multi-energy and storage collaboration system reduces the carbon emissions and system operational cost while ensuring power load requirements. Given the current cost of technology, increasing the penetration of intermittent renewable energy will still result in higher system costs and increased dispatch pressure on the grid. The thermal power unit is the cornerstone of the power grid system and replenishes the peak power load.

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