

Designing Flexible Electric Generation Portfolios in Iowa

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Abstract

Designing flexibility in electricity generation is important for power planning for the future. Creating electric power portfolios is a difficult engineering economics problem due to cost and other uncertainties. The flexibility of planning represents the capability to modify electricity generation under different kinds of conditions. The main challenge of electricity generation is uncertainty in the future. Uncertainties bring various scenarios that need to be considered for electricity generation. Uncertainties include the future demand, the investment cost, the fuel cost, the requirements for using renewable sources, and the future carbon emission limit. Monte Carlo simulation can simulate different scenarios caused by uncertainties. Making decisions to minimize the expected cost with too many scenarios encounters the curse of dimensionality. In addition, for long-term planning in electricity generation, dynamic decisions are required at different periods in the future. Therefore, based on all challenges and requirements for electricity generation, we present two methods, myopic planning and deep reinforcement learning, to solve the challenges. The objective of electric generation planning is to minimize the total cost which includes investment cost, operations, and maintenance cost, cost of fuel generation, and salvage value. The constraints consist of demand, requirements to use renewable resources, and limit on carbon emissions. The myopic planning and deep reinforcement learning methods are applied to electricity generation in the state of Iowa. The results demonstrate the advantages and disadvantages of using myopic planning and deep reinforcement learning.

Keywords:

Electric generation, Uncertainties, Flexibility, Planning

1. Introduction

Electricity power generation is affected by difference sources of uncertainties. Renewable energy power resources such as wind and solar power are becoming more prevalent. The uncertainty of weather will have impact on electric generation. The wind speed varies during a day and across different seasons. The basic goal of electric generation is to meet customer demand. With the increasing population, the overall consumption of electricity will likely increase in the future. The variation of future demand introduces uncertainty to electric generation. In addition to the weather and demand, the changing price of the power source (gas) and modified carbon emission limits should be considered for electric generation. Since various uncertainties exist, static planning is insufficient to plan for future electricity needs. A flexible electric generation portfolio is able to provide a more reliable planning for the future.

In engineering economics, common methods used to solve decision making under uncertainty are stochastic programming, robust optimization, and regret minimization. In this research, we formulate the electric generation problem as a stochastic programming problem. Instead of using traditional methods to solve the stochastic optimization, such as scenario reduction, we simulate different scenarios through Monte Carlo simulation. Two methods are used to solve the optimization problem. The first is myopic planning. The second one is deep reinforcement learning method. We apply our optimization model and solving methods to the electric generation in the state of Iowa.

2. Problem Description

The optimization model we use is taken from Mejia-Giraldo and McCalley [1]. The total cost of electric generation includes the cost of new generating capacity added to the current system Cap^{add} , the fixed cost of facility operation and the variable operating and maintenance cost OM . In addition, we also consider the cost of fuel \bar{FC} , such as natural gas and coal. The salvage value \bar{SV} is added to the total cost to capture the value of the installed capacity of the system

during the final planning period. The decision variables considered for the optimization problem are newly added capacity Cap^{add} , the installed capacity Cap , and power P generated at each time period. In our research we consider one region, Iowa. The objective function used in our research is:

$$\begin{aligned} \min & \sum_{j,t} \zeta^{t-1} \tilde{I}_{j,t,w} Cap_{j,t,w}^{add} \\ & + \sum_{j,t} \zeta^{t-1} (OM_{j,t}^{fixed} Cap_{j,t,w} + OM_{j,t}^{variable} \sum_s P_{j,s,t,w} h_s) \\ & + \sum_{f,t,s} \zeta^{t-1} \tilde{F}\tilde{C}_{f,t,w} (\sum_m H_m P_{m,s,t,w} h_s) - \zeta^{T-1} \sum_j \tilde{S}\tilde{V}_{j,w} Cap_{j,T,w}. \end{aligned} \quad (1)$$

The parameter j represents different technology used for electric generation. In the case in Iowa, we select the most widely used technologies, coal, natural gas, nuclear, wind, and hydro power. The parameter t is the time period of planning. The parameter w represents different scenario due to uncertainties. The parameter s represents different demand profiles during a single planning period. The parameter m denotes fuel-based technology, T is the planning horizon, and \tilde{I} is the investment cost based on scenario w . The O&M cost consists of OM^{fixed} cost and $OM^{variable}$ cost. H is the heat rate of a technology, and h represents the duration of each demand profile.

In our research, the objective is to minimize equation (1) subject to seven constraints for electric generation planning. The installed capacity of the system equals the sum of the existing capacity and the newly added capacity at each time period t .

$$\begin{aligned} Cap_{j,t,w} &= Cap_{j,t-1,w} + Cap_{j,t,w}^{add}, \quad \forall j, t \\ Cap_{j,t,w}^{add} &\geq 0, \quad \forall j, t \\ Cap_{j,0,w} &= Cap_j^{existing}, \quad \forall j \end{aligned} \quad (2)$$

The installed capacity needs to satisfy the peak demand for each time period t .

$$\sum_j Cap_{j,t,w} \geq (1+r) \tilde{d}_{peak,t,w}, \quad \forall j \quad (3)$$

For each technology at a different demand profile s during each time period t , the power generation is limited by the currently available capacity which is described by capacity credit $\tilde{C}\tilde{C}$. For example, different weather causes the variation of available energy used to generate electricity.

$$\tilde{C}\tilde{C}_{j,s} Cap_{j,t,w} \geq P_{j,s,t,w}, \quad \forall j, s, t \quad (4)$$

In addition, for each time period t , the total power generation is limited by the average generation level which is captured by the capacity factor $\tilde{C}\tilde{F}$.

$$\tilde{C}\tilde{F}_j Cap_{j,t,w} \sum_s h_s \geq \sum_s P_{j,s,t,w} h_s, \quad \forall j, t \quad (5)$$

The generated power must be at least equal to the demand.

$$\sum_j P_{j,s,t,w} \geq \tilde{d}_{s,t,w}, \quad \forall s, t \quad (6)$$

In order to ensure the renewable resources to be used for power generation, $\tilde{\rho}$ denotes the percentage of total generation from renewable energy sources,

$$\sum_{u,s} P_{u,s,t,w} h_s \geq \tilde{\rho}_{t,w} \sum_{j,s} P_{j,s,t,w} h_s, \quad \forall t \quad (7)$$

where u is the nonfuel-based renewable generation technology. The last constraint considers the carbon emission limitation for power generation.

$$\sum_{j,s} E_j P_{j,s,t,w} h_s \leq \widetilde{CO}_{t,w}^{cap}, \quad \forall t \quad (8)$$

3. Related Research

The most commonly used method for electric generation planning with uncertainty is stochastic programming. Two typical models of stochastic programming are two-stage stochastic optimization [2]-[4] and multi-stage stochastic optimization [5, 6]. For electric generation planning, the two-stage stochastic optimization splits the problem into two parts for electric generation planning. In the first stage, the investment decision is made without considering any uncertainty. The first stage plans the investment for the whole planning period. The second stage is operational decision. The value of decision variables for the second stage depend on the uncertain scenarios [7]-[10]. For the multi-stage stochastic optimization, both investment and operational decisions are made by considering uncertainty at different stages [11]-[14].

The biggest challenge for solving the stochastic optimization problem is the large number of uncertain scenarios. With a large number of uncertainties, finding the optimal solution is computationally expensive for both two-stage and multi-stage stochastic optimization problems. Selecting the most representative scenarios can reduce the computation time. Several scenario reduction methods can be found in the existing literature, such as the fast forward selection and the simultaneous backward reduction [15-18]. Some decomposition methods are proposed to help solve multi-stage stochastic optimization more efficiently. Scenario-based decomposition methods include dual decomposition [19, 20] and progressive hedging [21, 22], and stage-based decomposition methods include stochastic dual dynamic programming [23, 24].

Despite these methods, limitations still exist. The scenario reduction method eliminates uncertain scenarios. The number of required scenarios needs to be decided before using the reduction algorithm. The selected scenarios might ignore the useful information of eliminated scenarios. Dynamic programming is frequently realized by parallel computing, which requires careful coding to enable parallel computing to operate efficiently.

4. Methodology

Our research uses myopic planning and deep reinforcement learning to solve the energy planning problem with the objective of minimizing the expected cost. Myopic planning refers to decision making that focuses on optimizing for the current period [25]. We combine the Monte Carlo simulation with myopic planning to generate long-term planning for electric generation. A long-term planning horizon consists of several time periods. For the first period, every uncertain parameter of optimization starts with the fixed value. After the first period, we use Monte Carlo simulation to simulate different realizations of uncertain parameters. Myopic planning solves the static optimization given the values of uncertain parameters for the next time period. The simulation generates different uncertain decision-making scenarios for the whole planning horizon. For every simulated uncertain scenario path, the static optimization provides the optimal planning portfolio for the whole planning horizon. We create the flexible electric generation portfolios using the simulated paths with corresponding optimal generation planning results.

The second method is using deep reinforcement learning to design flexible electric generation portfolios. Unlike myopic planning method, deep reinforcement learning provides the optimal generation planning for each simulated uncertain scenario using the learned neural network [26, 27]. The neural network is trained by the action and reward pairs. In our research, we choose to use the deep Q-learning to train the neural network [28, 29]. The Q function of Q-

learning captures the approximate objective function value at each time period. For each time period over the whole planning horizon, the action taken for electric generation is selected through a ε -greedy decision-making policy. The value of ε is between 0 and 1. During Q-learning, the ε -greedy decision-making policy chooses an action having maximum reward with the $1 - \varepsilon$ probability. The random action is made with ε probability. Once the neural network is well trained by Q-learning with the ε -greedy policy, the expected reward value over the fixed number of simulated uncertain scenarios will converge.

5. Application

The data we use for Iowa case study is from Mejia-Giraldo and McCalley [1] and online sources. The existing capacity and generation data is from the Iowa’s Electric Profile [30]. For the capacity factor \widetilde{CF} , we integrate an online source [31] and values provided by [1] to use as input into optimization model. The emission data of the fuel-based electric generation technology, coal and natural gas, is obtained from the U.S. Energy Information Administration [32]. We use the carbon emission limits based on Iowa’s Pathway to Cutting Carbon Pollution report [33]. The overall planning horizon we choose for Iowa is 10 years. Each time period of the planning horizon consists of 2 years. Each time period is divided into 3 demand profiles. The uncertainties considered for Iowa electric generation are the investment of wind power $\tilde{I}_{WIND,t,w}$, the demand for each time period $\tilde{d}_{t,w}$, the renewable power source percentage $\tilde{p}_{t,w}$, and the carbon emission limit $\tilde{CO}_{t,w}^{cap}$. We denote the change rate for a certain scenario is μ_w . The current realization of an uncertain parameter $\chi_{t,w}$ is calculated by $\chi_{t,w} = \chi_{t-1,w}(1 + \mu_w)$. For each uncertain parameter, two potential change rates are considered. The transition probabilities between two change rates for each uncertain parameter is taken from [1]. We use the transition probabilities and Monte Carlo simulation to simulate uncertain scenarios for each time period.

We compare the computation performance between myopic planning method and deep reinforcement learning method. For planning 4 years, 2 time periods, the running time of deep reinforcement learning is much longer than the myopic planning. Because myopic planning only involves a linear optimization calculation. The deep reinforcement learning consists of two parts, the neural network training and optimization calculation. In order to let the neural network learn as many potential scenarios as possible, we need to have at least tens of thousands of replications. The deep reinforcement learning results in a much longer computation time than the myopic method.

Myopic planning is used to design flexible electric generation portfolios for 10 years in Iowa. Based on the data from the Iowa Utilities Board [30], Iowa’s existing generating capacity can always satisfy the demand. We assume that the fuel-based technology using coal and natural gas will need to retire in next 10 years to reflect carbon neutral goals. We simulate 1000 scenarios. The total number of unique simulated scenarios is 609. Based on all solutions provided by myopic planning, Iowa should add capacity in wind power but keep hydro power capacity constant. **Figure 1** presents the mean capacity to be added in wind power during each time period over 10 years (5 periods) under low, medium, and high demand scenarios. Myopic planning combined with Monte Carlo simulation is able to provide flexible generation portfolios to deal with a variety of uncertain scenarios within a reasonable time.

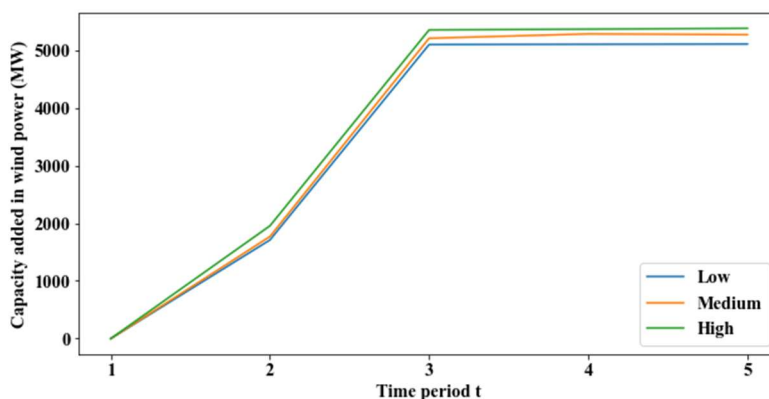


Figure 1: Capacity added in wind power under different demand scenarios

6. Conclusions

Our research provides methods to design flexible electric generation portfolios. The myopic planning combined with Monte Carlo simulation avoids the elimination of useful information caused by the scenarios reduction algorithm. Compared with similar dynamic decision-making process realized by deep reinforcement learning, the myopic method provides planning results within a reasonable time. The myopic method is simple and fast to use as generation planning tools and may be reasonable for the electricity planning problem where the objective function is separable. Additional GPUs could be used to improve the training time of the neural network in deep reinforcement learning or conduct parallel computation of dynamic programming in stage-based decomposition algorithm.

The improvement of this research can be considered in several directions. More research needs to be conducted in order to generate accurate solutions in the reinforcement learning as applied to electricity generation planning and to understand the conditions when reinforcement learning provides better insights than myopic planning. The present research considers five main energy sources in Iowa: coal, natural gas, wind, hydro, and nuclear. Future research could include additional energy sources such as solar power and petroleum.

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