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Short communication

Economic evaluation of private power production under uncertainties

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Abstract

Private power production is becoming an increasingly important source of electricity generation. In developing countries, build–operate–transfer (BOT) arrangement has emerged as a dominant form of private investment. Pricing private power production at its avoided cost is the breakeven point for the utility in economic evaluation, and uncertainties must be taken into account. In this paper, an approach of calculating the breakeven cost to the utility of a BOT power plant whose contract lasts for 10–25 years is proposed. The proposed approach requires the computation of production costs from long-term generation expansion planning (GEP) under future uncertainties. To facilitate the inclusion of constraints introduced by BOT plants in GEP and uncertainties, a genetic algorithm method is utilized in GEP. The breakeven cost is a useful measure in the economic evaluation of BOT power plants. An example is presented to illustrate the economic evaluation of BOT plants using the concept of breakeven cost.

Keywords: Private power production; Build–operate–transfer; Generation expansion planning; Uncertainties; Genetic algorithms

1. Introduction

Private power production is becoming an increasingly important source of electricity generation. Build, operate and transfer (BOT) arrangement has been considered an attractive model and has gained widespread popularity in developing countries, especially Asia, such as the 700 MW Shajiao-B power stations in China, 1200 MW Hab River project in Pakistan, 300 MW coal-fired projects in Philippines and 1000 MW Aliaga project in Turkey [1–3]. Briefly, BOT arrangement is one where a private power development consortium, usually foreign, raises the finance and builds a power plant whose output is purchased by an electric power utility in the host nation. At the end of the franchise period, typically between 10 and 25 years, ownership of the plant is transferred to the host utility or government, usually for a token payment. There are some variations, such as build, operate and own (BOO). Here we call them BOT for generality. The BOT arrangement provides a 'costless' start-up for financially constricted governments [1,2], and is therefore considered attractive. However, it may impose significant long-term financial liability.

To mitigate future risks a BOT power plant usually asks for an energy contract, which stipulates the delivered energy amount, price and time periods. For example, in the Shajiao-B project the Chinese agreed to purchase a minimum of 60% of the plant capacity (power off-take) annually on a 'take and pay' basis, and pay a fixed price per kilowatt hour for the whole of the 10-year cooperation period. Due to the long-term nature of the contract, the utility must evaluate a BOT power plant considering its long-term impacts on the future flexibility of system capacity addition and operation. Long-term generation expansion planning (GEP) is such a suitable tool for the economic evaluation of BOT power plants. Some papers [4–6] discussed the integration of non-utility generation into generation expansion planning of utilities. Furthermore, inevitable future uncertainties accompanying GEP, such as load growth rates, fuel costs, etc. must be taken into account in the evaluation. There are many lessons from utilities without deliberated consideration about uncertainties. Therefore, much work has been done to deal with uncertainties in GEP [10–13].

This paper concentrates on the pricing of BOT energy contracts. It is argued that the utility should pay for the private power generation at a rate which is commensurate with what it would cost the utility to generate that same excess energy using its own facilities, i.e. 'avoided cost'. However, this definition is too vague to directly implement. In US and Canada, controversies surrounded the calculation of avoided costs for non-utility generation [7–9], and different interpretations and implementations have been

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adopted by electric utilities. To date, old contracts with non-utility generation still have great impact on the operation and development of electric utilities [9]. In addition, future uncertainties are little concerned in the 'avoided cost' concept. BOT arrangement is a special type of private power production where BOT power plants can only sell their power to the host utility by energy contracts usually without fixed capacity payment. Therefore to a utility, a suitable method to evaluate the long-term avoided cost of a BOT power plant under uncertainties is needed.

In this paper, a 'breakeven cost' concept for BOT power plants is proposed, and GEP is used to calculate the breakeven cost of a BOT Energy contract, as described in later section. It needs an effective and robust approach for GEP, which should easily include BOT constraints and uncertainties. GEP is a highly constrained non-linear discrete dynamic optimization problem, and uncertainty makes this problem more difficult. To solve this complicated problem, a number of approaches have been developed successfully during the last decades. Stochastic dynamic programming and decomposition approaches are among the most popular methods [10–14]. However, there are still some difficulties in the application and effectiveness of these methods to practical GEP problems, such as dynamic programming, 'curse of dimensionality' hinders its practicability for large systems. Recently, some new approaches are examined. A review of emerging techniques on GEP is given in Ref. [15]. Among them, evolutionary algorithms have shown a promising prospective [16,17], which not only can treat the discrete variables easily, but also overcome the dimensionality problem faced by dynamic programming. In addition, they have the capability to search for the global optimum and high suitability for parallel computation. However these evolutionary algorithms for GEP are deterministic without uncertainties analysis. Even though they can be used as a tool for scenario analysis, it is more convenient and suitable to integrate uncertainties directly into the GEP modeling.

In this paper, a long-term breakeven cost of BOT is defined based on GEP. Furthermore, a genetic algorithm (GA) approach for GEP is developed which can easily incorporate uncertainties and BOT constraints. Finally, the suggested economic evaluation of BOT power plants is applied to an illustrative system with 28 existing power units, 4 types and total 40 units of candidate units.

2. Cost-benefit analysis of BOT power production

A utility may plan future generation addition from various resources such as coal, oil, nuclear, LNG, etc. Furthermore, different generation types, such as base, middle and peak type will also be considered. As deregulation is popular all around the world, private power production, such as BOT, has become an important part of generation resources. In order to evaluate the economic impact of a BOT energy contract from the viewpoint of long-term GEP, the breakeven cost of BOT is defined, which is the price for an electric utility willing to pay for BOT's electricity. The breakeven cost of BOT can be treated as a long-term 'avoided cost'.

Assume EC_0 and EC_B is the expected total generation expansion cost of the utility without BOT and with BOT during the planning horizon, we define the breakeven cost of BOT as follows

$$\text{Breakeven cost} = \frac{\mathrm{EC}_0 - \mathrm{EC}_\mathrm{B}}{T_\mathrm{B}\bar{Q}_\mathrm{B}} \tag{1}$$

where $\bar{Q}_\mathrm{B}$ is the annual contracted minimum energy generated by BOT during the planning horizon, and T_B is the BOT power plant life in the planning horizon. It should be noted that all quantities in Eq. (1) are calculated based on present values.

The breakeven cost implies that a utility purchases a BOT's electricity in such a way that the utility's total generating cost should not change before and after the entry of a BOT. Of course, the utility will make some changes referring the breakeven cost according to corresponding policies in order to attract private investors.

In addition, sensitivity analysis must be performed further to examine the capacity and/or energy changes of the BOT plant. The original generation mix of GEP may be changed when the BOT is introduced in different intervals and load factors.

3. Mathematical formulation of GEP under uncertainties

To calculate the breakeven cost of a BOT power plant, GEP under uncertainties must be performed. Optimal (GEP) is to determine the least-cost capacity addition schedule that satisfies forecasted load demands within the given reliability criteria over a planning horizon. Therefore, the objective function of least-cost GEP problem is to minimise the expected sum of costs including construction costs and operation costs. The GEP problem is mathematically formulated as follows.

3.1. Objective function

$$\min z = \underset{Q_{ij}}{E}\left\{\sum_{i=1}^{T}\left[\sum_{j=1}^{M}(a_j x_{ij} + b_j Q_{ij})\right]\right\} \tag{2}$$

$$X_{ij} = X_{i(j-1)} + x_{ij} \quad (i = 1,2,\dots,T, j = 1,2,\dots,M) \tag{3}$$

$$\phi_{ij} = \sum_{k=1}^{j} X_{ik} \quad (i = 1,2,\dots,T, j = 1,2,\dots,M) \tag{4}$$

$$Q_{ij} = \int_{\phi_{i(j-1)}}^{\phi_{i(j-1)}+X_{ij}} L_i(u)\mathrm{d}u \quad (i = 1,2,\dots,T, j = 1,2,\dots,M) \tag{5}$$

where $E[\,]$ is the expection operator; T, the number of time intervals; M, the total number of technologies; a_j, the fixed cost coefficient of technology j; b_j, the variable cost coefficient of technology j; x_{ij}, the introduced amount (MW) of technology j at interval i; X_{ij}, the total introduced amount of technology j till interval i; Q_{ij}, the total energy output (MW h) of technology j at interval i; ϕ_{ij}, the loading point of technology j at interval i; L_j is the load duration curve at interval i.

The objective function (2) is to minimise the sum of discounted fixed (investment) cost and variable (operation) cost over the planning horizon. Each x_{ij} is a decision variable assumed to have discrete values. If a specified mix of investments, i.e. matrix $\{x_{ij}\}$, is given, the problem is reduced to a operation subproblem. The solution methods to the operation problem depend on the degree of simplifying the problem. Merit order, linear programming and dynamic programming are among the most common methods. In this paper, merit order is adopted using Eqs. (3)–(5).

3.2. Constraints

(1) Maximum and minimum capacity limits

$$x_{j,\min} \le x_{ij} \le x_{j,\max} \quad (i = 1,2,\ldots,T, j = 1,2,\ldots,M) \tag{6}$$

where $x_{j,\min}$ is the minimum capacity of technology j and $x_{j,\max}$ is the maximum capacity of technology j.

(2) Supply and demand balance

Uncertain load makes it difficlut to guarantee the demand to be met at all times, so a more convenient way is to introduce a penalty cost function that transfers unserved load to economic loss in the penalty function.

$$\mathrm{EL} = pf(L_\mathrm{u}) \tag{7}$$

EL is the economic loss due to unserved load; L_u, the total unserved load and pf is the penalty function.

(3) Cost coefficient constraints

$$b_j \le b_{j+1} \quad (j = 1,2,\ldots,M) \tag{8}$$

3.3. Additional BOT constrains

We incorporate two additional constraints into our GEP model for a BOT unit:

$$x_\mathrm{B} \le \bar{x}_\mathrm{B}(\text{MW capacity}) \tag{9}$$

$$Q_\mathrm{B} = \bar{Q}_\mathrm{B}(\text{annual contracted energy})$$

Without BOT's entry, each unit including existing and newly introduced units will be loaded by a 'merit order'. After a BOT power plant enters, a fixed load factor of the BOT unit has been given and must be guaranteed. Therefore, firstly we search the loading point of a BOT plant to satisfy its load factor based on load duration curve in each interval, and then determine the loading points of other units according to 'merit order'.

3.4. Uncertainties

Many sources of uncertainty may have an important impact on GEP by different future supply conditions, which include load growth rate, fuel costs, construction costs, financial constraints, etc. In this paper, for simplicity we only consider the load growths rate as uncertain variable, and other uncertainties can be treated similarly.

Due to the same reasons as in Ref. [12], this uncertain variable is modeled by Markov chains as shown in Fig. 1.

4. Genetic algorithm approach for GEP

GAs are stochastic algorithms whose search methods model some natural phenomena: generic inheritance and Darwinian strife for survival. GAs, differing from conventional search techniques, start with an initial set of solutions called population. Each individual in the population is called a chromosome, representing a solution to the problem. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated, using some measures of fitness. To create the next generation, new chromosomes, called offspring, are formed by either (a) merging two chromosomes from current generation using a crossover operator or (b) modifying a chromosome using a mutation operator. A new generation is formed by selecting some of the parents and offsprings, according to the fitness values. Fitter chromosomes have higher probabilities of survival. After a predetermined number of generations, the algorithms converge to the best chromosome, hopefully representing the optimum or near-optimum solution to the problem. GA is robust because no restrictions on the solution space are made. GA can handle any kind of objective functions and any kind of constraints defined on discrete, continuous, or mixed search space.

In general, a GA for a particular problem must have the following five components: (1) a genetic representation for potential solutions to the problem, (2) a way to create an initial population of potential solutions, (3) an evaluation function that plays the role of the environment, rating solutions in terms of their 'fitness', (4) genetic operators that alter the composition of children, and (5) values for various

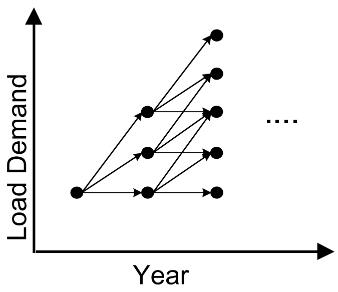

Fig. 1. A discrete Markov chain for load demand.

Table 1
An example of chromosome

Technology 1		···	Technology I				···	Technology M					
2	3		2	5	5	5		0	0	0	0	0	0

parameters that the GA uses (population size, probabilities of applying genetic operators, etc.)[18].

4.1. String representation and constraint handling

How to encode a solution of the problem into a chromosome is a key issue for GA. The same string representation as in Ref. [16] is used which has the following features:

- The length of a chromosome equals to the number of total newly introduced generation units.
- Each gene represents the introduced time interval of each unit.

For example, in Table 1, the technology type 1 has two units which will be introduced in intervals 2 and 3, and technology type M has 6 units which will not be introduced (0 represents not introduced). Integer encoding is used thanks to its convenience for a combinatorial optimization problem. If the capacity limit (6) is violated, the chromosome will be repaired to round into the limit.

4.2. Creation of initial population

Initial strings in the population are generated randomly. The distribution of initial strings is uniform in this paper, and has the tendency of spreading out over intervals. Therefore, this random creation of initial population is appropriate for the specific string representation.

4.3. Evaluation and selection

The fitness value of a string is calculated using

$$f = \frac{\alpha}{z} \tag{10}$$

where α is a constant, and z is the objective function value of Eq. (2).

To avoid premature convergence, the following modified fitness function, which normalizes the fitness values of strings into real numbers within [0,1], is used in this paper.

$$f' = \frac{f - f_{\min}}{f_{\max} - f_{\min}} \tag{11}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and minimum fitness values in a generation.

In this paper, Roulette wheel selection (RWS) and Tournament selection are tested. In addition, the selection scheme might not give a set of dominant member the chance to reproduce, and string operations will increase the probability of destroying string structures of an elite group. To mitigate this unfavorable effect to some extent, an elitism mechanism is applied to make sure that the best chromosomes in the present generation are kept in the next generation.

4.4. String operation

The crossover used here is a simple one-point crossover. In mutation operation, an interval number other than the current interval is selected randomly among the maximum and minimum intervals. Crossover leads to population convergence while mutation helps to maintain diversity. To prevent premature convergence or excessive diversity, a dynamic adjustment mechanism of probabilities for string operation is used. The convergent situation is monitored by statistical information from the population in generations. When premature convergence occurs, the crossover probability is decreased while mutation probability is increased. For excessive diversity, the reverse adjustment is carried out.

4.5. Calculation of annual variable costs

In fact, the GA method decomposes the GEP problem into two levels: the upper is to determine the optimal generation mix by GA search, and the lower is to calculate total costs. For a given generation mix, i.e. a chromosome, the total fixed cost can directly be calculated, and the variable cost for each year can separately be calculated based on the 'merit order' loading scheme. It should be noted that there is only a little difference in the 'merit order' loading schemes between GEP without BOT and GEP with BOT. In addition, uncertainties are only concerned in the calculation of annual variable costs. Therefore, the GA method for GEP is straightforward extendable in respect to BOT constraints, uncertainties and other considerations.

Based on the comparisons between GA approaches and conventional GEP approaches reported in Refs. [16,17], we are convinced that our GA method should have a better performance than other conventional methods.

5. Numerical examples

The proposed method has been applied to an example system, which is a modification from Ref. [16]. The initial system, candidate plants and load data are listed in

Table 2
Parameters of the test system

Technology	Variable cost (yen/MW h)	Fixed cost (yen/kW)	Unit capacity (MW)
Nuclear	5	65,000	1000
Coal	8	45,000	500
LNG	10	40,000	300
Thermal	15	35,000	200

Table 3
Existing and candidate units

Technology	Existing units	Candidate units
Nuclear	4	2
Coal	6	10
LNG	4	10
Thermal	14	18

Table 4
Load duration curve

Interval	Peak load (MW)	Base load (MW)	$L^{-1}(x) = (x-d)^2/c$	
			$c \times 10^4$	$d \times 10^4$
Present	10,000	3500	0.4821	1.0

Tables 2–4, and a 15-year planning period is considered, which is divided into 5 time stages, each of 3 years duration.

In the Table 3, plant types 1 and 2 are base plants while type 4 is a peak plant. The load duration curves are approximated with a second order function of loads. Peak loads and base loads are assumed to have same growth rates. The reserve is assumed to be 10% of the peak load. Three states of load growth rates are considered in Fig. 2: low-2%, middle (more possible)-4%, and high-6%.

The parameters for GA are as follows:

String representation: integer coding
Selection method: Roulette wheel selection (RWS), Tournament selection
Crossover probability: 0.8–0.2
Mutation probability: 0.01–0.1
Initial population: 50
Maximum generation: 300

Case 1: without BOT

First the total expected cost of GEP without BOT power plant is calculated, and total 6.6519 Myen is obtained.

Case 2: BOT 1

Then a unit of type 4, which is a peak type unit, is selected as a BOT power plant, and is assumed to be installed in the third stage, and its load factor is 0.1 (for full capacity). Its breakeven cost is 15.4 yen/kW h.

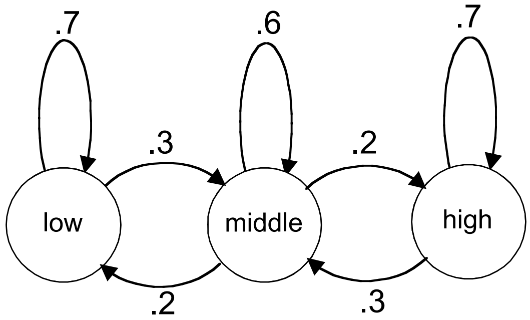

Fig. 2. State model of the Markov chain for load growth rate.

Case 3: BOT 2

This time, the same unit as BOT1 is selected, but its load factor is increased to 0.3. Its breakeven cost is 11.3 yen/kW h.

Case 4: BOT 3

Finally BOT 2 is brought forward to the first time interval. Its breakeven cost is 10.3 yen/kW h. Here we should point out that BOT3 has more total fixed cost due to its early introduced interval.

We should also mention that many of type 4 units are installed for system reserve. The above cases show that the introduced interval and load factor of BOT plant have important effects on GEP. In case 2, an unit which is in the generation mix of the original GEP and at the same interval was selected as a BOT, and its load factor is closer to that in the original GEP. In the case 3, the same BOT but different load factor was evaluated. Because it is a peak type of unit, so its load factor in the original GEP is relatively lower. Increase of its load factor lets it to generate more electricity, however the breakeven cost is decreased. In these two cases, the combination of other units is the same as that in the original GEP, but it is possible that change of BOT load factor would make the combination of other units deviated. In case 4, the BOT plant was brought forward to interval 1 from interval 3, it is seen that another unit of type 3 is delayed from interval 2 to interval 3, and was replaced by a unit of type 4, so the original combination of generation units was disturbed. The BOT in this case increases the total cost of utility for generation addition by itself. Therefore, the breakeven cost of the BOT plant is much low.

Actually a unit of base type (type 2, coal) is also selected as a BOT to install in its original interval, and assign its load factor to be 1. Obviously there are no influences on the original GEP. Therefore, the BOT can get maximum benefit based on our approach. So BOT investors will be encouraged to build base type of plants.

6. Conclusions

As a dominant form of private investment, build–operate–transfer (BOT) arrangement has been drawing much attention. In the economic evaluation of BOT energy contracts, pricing BOT generation at its avoided cost is the breakeven point for the utility, meanwhile uncertainties must be taken into account. In this paper, the breakeven cost of a BOT power plant is defined, and an approach of calculating the breakeven cost to the utility is proposed. The proposed approach requires the computation of production costs from GEP under future uncertainties. To facilitate the inclusion of BOT constraints and future uncertainties, a GA approach is developed for GEP.

The breakeven cost is a useful measure in the economic evaluation of BOT power plants. Our suggested economical evaluation model is illustrated through case studies. It has been shown that the installation intervals, load factor and capacity of a BOT power plant will influence the GEP results significantly, and sensitivity analysis on these factors should be conducted in the evaluation.

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