Cost-benefit Analysis of BOT Power Plants

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Abstract: Among non-utility generation, Build-Operate-Transfer (BOT) arrangement has emerged as the dominant form of private investment. Pricing non-utility generation at its avoided cost is the breakeven point for the utility in the cost-benefit analysis. In this paper, a method if calculating the breakeven cost to the utility for BOT plants 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). To facilitate the inclusion of constraints introduced by BOT plants in GEP, a genetic algorithm approach is utilized in GEP. The breakeven cost is a useful measure in cost-benefit analysis of BOT power plants. An example is presented to illustrate cost-benefit analysis of BOT plants using the concept of breakeven cost.

Keywords: Build-Operate-Transfer (BOT), Generation Expansion Planning, Genetic Algorithms

I. INTRODUCTION

Private power production is becoming an increasingly important source of electricity generation in developing countries. A build, operate and transfer (BOT) arrangement is considered an attractive model gaining widespread popularity especially in Asia, such as the 700MW Shajiao-B power stations in China, 1200MW Hab River project in Pakistan, 300 MW coal-fired projects in Philippines and 1000 MW Aliaga project in Turkey [2,3].

Simply stated, a BOT arrangement is one where a private power development consortium, usually foreign, raises the finance and builds a power station 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), we call them BOT for generality. The BOT arrangement provides a "costless" start-up for financially constricted governments [1], and is therefore considered attractive. However the contract may impose significant long-term financial liability.

Among many contracts between a BOT plant and a host utility, the agreement on how much energy is to be delivered, at what prices and during what time periods is very basic [3], for example, in the Shajiao-B project the Chinese agreed to annually purchase a minimum of 60% of the plant capacity (power off-take) on a "take and pay" basis, and pay a fixed price per kilowatt hour for the whole of the then-year cooperation period. Usually such a contract is long-term, the utility must evaluate the long-term influence of a BOT power plant on the system capacity and operation. Therefore, cost-benefit analysis of BOT should take into account this impact on the long-term generation expansion of a host utility. Previous papers [3,5] discussed the integration of non-utility generation into generation expansion planning of utilities. It is argued that the utility should pay for 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". A method to evaluate the long-term avoided cost of BOT power plant to the utility is needed.

In addition, a GEP problem is a highly constrained non-linear discrete dynamic optimization problem. A number of salient methods were developed successfully during the past decades, and dynamic programming is one of the most popular methods [6,7,8,9,10]. However, there are still some difficulties in the application of these methods to practical GEP problems. Recently, genetic algorithms (GA) are applied on this problem, and shows a promising prospective [11, 12]. GA-based approaches for GEP can not only treat easily the discrete variables, 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.

In this paper, a long-term breakeven cost of BOT, which is the basic cost of BOT paid willingly by the utility for BOT's generation, is defined based on long-term GEP. Furthermore, a GA approach for GEP is developed which can easily incorporate BOT's constraints. Finally, the suggested cost-benefit analysis of BOT is applied to an illustrative system with 15 existing power plants, 5 types and total 60 units of proposed plants.

II. COST-BENEFIT ANALYSIS OF BOT

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 be considered also. With the BOT's entry, the original GEP will be affected. In order to evaluate the economic impact of BOT from the viewpoint of long-term GEP, the breakeven cost of BOT is defined in this paper, which is the basic price for an electric utility to pay for BOT's electricity. The breakeven cost of BOT can be treated as the long-term "avoided cost".

Assume C_0 and C_B is the total generation cost of the utility without BOT and with BOT during the planning horizon, we define the breakeven cost of BOT as follows:

$$Breakeven\cos t = \frac{C_0 - C_B}{T\bar{Q}_B} \quad (1)$$

here, $\bar{Q}_B$ is the annual contracted energy generated by BOT during the planning horizon, and T is the number of time intervals during the planning horizon.

It should be noted that all quantities in Eq. (1) are calculated based on [resent value. The calculation of C_0 and C_B involves GEP.

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.

Meanwhile, sensitivity analysis must be performed further to examine the capacity and/or energy changes of the BOT plant. The original GEP may be changed when the BOT is introduced in different intervals and load factors. Similarly, whether the BOT unit is one in the original GEP generation mix or not.

III. MATHEMATICAL FORMULATION OF GEP

To calculate the breakeven cost of BOT, GEP must be performed, and the original GEP problem will be complicated by BOT's constraints.

Optimal long-term generation expansion planning 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 the expected sum of costs including construction costs and operation costs. The GEP problem is mathematically formulated as follows:

Objective function

$$\min z = \sum_{i=1}^{T}[\sum_{j=1}^{M}\{a_j(X_{ij} - X_{0i}) + b_j Q_{ij}\}] \quad (2)$$

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

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

$$Q_{ij} = \int_{\phi_{i(j-1)}}^{\phi_{i(j-1)}+X_{ij}} L_i(u)du \;\; (i=1,2,\ldots,T, j=1,2,\ldots,M) \quad (5)$$

Where

T: the number of time intervals

M: the total number of technologies

a_j : fixed cost coefficient of technology j

b_j : variable cost coefficient of technology j

x_{ij} : introduced amount (MW) if technology j at interval i

X_{ij} : total introduce amount of technology j till interval i

X_{ij} : total generation amount of generation technology j at the current interval

Q_{ij} : total energy output (MWh) of technology j at interval i

ϕ_{ij} : the loading point of technology j at interval i

L_j : load duration curve at interval i

The objective function (2) is a sum of fixed cost and variable cost discounted over the planning horizon. Each x_{ij} is a decision variable assumed to have discrete values. From equation (5), it can be seen that the loading points of each unit is determined using "merit order".

Constraints

(1) maximum and minimum capacity of proposed unit

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

where

$x_{j,\min}$: minimum capacity of technology j

$x_{j,\max}$: maximum capacity of technology j

(2) supply and demand balance

$$\sum_{k=1}^{M} X_{ij} \ge P_{Di} + P_{Ri} \;\; (i=1,2,\ldots,T) \quad (7)$$

where

P_{Di} : peak load at interval i

P_{Ri} : reserve at interval i

(3) cost codfficient constraints

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

Additional BOT constrains

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

$$x_B \le \bar{x}_B \ (MW\ capacity)$$
$$Q_B = \bar{Q}_B \ (annual\ contracted\ energy) \quad (9)$$

Without BOT's influence, each unit including existing and newly introduced units will be loaded by a "merit order". But after BOT 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, then fix the loading points of other units according to "merit order".

IV. THE GA APPROACH FOR GEP

A long-term GEP problem is a highly constrained nonlinear discrete dynamic optimization problem. Dynamic programming (DP) approach is one of the most popular algorithms in solving GEP problem. However, 'curse of the dimensionality' hinders the direct application of conventional DP to a practical GEP problem. Recently genetic algorithm is emerging as a promising approach for solving GEP problem.

Basically, GA is one of stochastic search algorithm based on Darwinian principle of natural evolution. In general, a GA for a particular problem must have the following five components: (1) a genetic representation for potential solution s 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 parameters that the GA uses (population size, probabilities of applying genetic operators, etc.) [13].

String structure

String representation is an important factor for GA. Because it is convenient to use integer values for implementation of a GEP problem, the string structure of Figure 1is used in this paper.

Table 1. An example of chromosome

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

Each gene in a chromosome represents a newly introduced unit, whose value is the interval at which the unit is introduced. The length of a chromosome equals to the number of total proposed generation units. For example, in Figure 1, the technology type 1 has two units which will be introduced in interval 2 and 3, and technology type M has 6 units which will not be introduced (0 represents not introducing).

Creation of initial population

Initial strings in the population are generated randomly, and a string is accepted if it satisfies constraints (1) and (2). Otherwise, this string is discarded and a new string is generated again. 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.

Evaluation and selection

The fitness value of a string is calculated using

$$f = \frac{\alpha}{z} \quad (10)$$

where α is a constant, and z is the objective function value of equation (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.

$$f' = \frac{f - f_{\min}}{f_{\max} - f_{\min}} \quad (11)$$

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

In this paper, conventional Roulette Wheel Selection (RWS) is used. In addition, RWS 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 is kept in the next generation.

String operation

When crossover and mutation are performed, strings that satisfy constraints (1) and (2) are generated. If a string violate the constraints, it will be discarded and string operation will be performed again.

The crossover used here is a simple one-point crossover. Only the combination of introduced intervals of total generation units can be changed by using the decimal coding. In mutation operation, an interval number other than the current interval is selected randomly among the maximum and minimum intervals.

V. NUMERICAL EXAMPLES

The proposed method has been applied to an example system, which is a modification from [11]. The initial system, proposed plants and load data are listed in Table 2, 3 and 4, and a 20-year planning period is considered, which is divided into 5 time stages, each of four years duration.

Table 2. Existing plant (15 units)

Plant Type	Energy Cost ($/MWh)	Max Cap (MW * No)
Oil #1 (heavy oil)	24	200 * 1
Oil #2 (heavy oil)	27	200 * 1
Oil #3 (heavy oil)	30	150 * 1
LNG G/T #1	43	50 * 3
LNG C/C #1	38	400 * 1
LNG C/C #2	40	400 * 1
LNG C/C #3	35	450 * 1
Coal #1 (anthracite)	23	250 * 2
Coal #2 (bituminous)	19	500 * 1
Coal #3 (bituminous)	15	500 * 1
Nuclear #1	5	1000 * 1
Nuclear #2	5	1000 * 1

Table 3. Proposed generation plant (60 units)

Plant Type		Energy Cost ($/MWh)	Capacity Cost ($/kW)	Max Cap (MW * No)
1	Nuclear (PHWR)	3	1750.0	700 * 3
2	Nuclear (PWR)	4	1625.0	1000 * 3
3	Coal	14	1062.5	500 * 18
4	Oil	21	812.5	200 * 18
5	LNG C/C	35	500.0	450 * 18

Table 4. Load duration curve

Interval	Peak load (MW)	Base load (MW)	$L^{-1}(x) = (x-d)^2/c$	
			$c * 10^3$	$d * 10^3$
Present	5000	2500	0.285	5

In the table 3, plant type 1 and 2 are base plants while 3, 4 and 5 are middle and peak plants. The load duration curve are approximated with a second order function of loads. Peak loads and base loads are assumed to increase 10% per year. The reserve is 1%. In addition, an annual discount rate of 10% for both capital and operating expenses are used. The parameters for GA are as follows:

String representation: decimal coding
Selection method: Roulette wheel selection (RWS)
Crossover probability: 0.6
Mutation probability: 0.05
Initial population: 50
Maximum generation: 1000

Case 1: without BOT

Table 5. Optimal expansion planning without BOT

Type	Stage 1	2	3	4	5
1	--	--	3	--	--
2	1	2	--	--	--
3	--	--	2	9	7
4	1	1	1	4	9
5	--	2	3	3	10
Total cost			12884 ($M)		

Case 2: BOT 1

A unit of type 5 is selected as a BOT plant, which is introduced in the second stage, and its load factor is 0.2, its capacity is 450MW.

Table 6. BOT 1

Type	Stage 1	2	3	4	5
1	--	--	3	--	--
2	1	2	--	--	--
3	--	--	2	9	7
4	1	1	1	4	9
5	--	1	3	3	10
Total cost			12611 ($M)		

Breakeven Cost: 21.64$/MWH

Here, the breakeven cost need to be explained more. Because the total cost of generation expansion is a present value after discounted, the breakeven cost is represented as a present value. The average present value of the energy cost and capacity cost of the BOT as a type 5 is 15.65$/MWh and 6.62$/MWh.

Case 3: BOT 2

It is the same as the above BOT plant but load factor is changed to 0.4.

Table 7. BOT 2

Type	Stage 1	2	3	4	5
1	--	--	3	--	--
2	1	2	--	--	--
3	--	--	2	9	7
4	1	1	1	4	9
5	--	2	3	3	10
Total cost			12510.6 ($M)		

Breakeven Cost: 14.8 $/MWH

Case 4: BOT 3

It is the same as the BOT 1 plant but being brought forward to the first stage.

Table 8. BOT 3

Type	Stage 1	2	3	4	5
1	--	--	3	--	--
2	--	3	--	--	--
3	--	--	2	9	7
4	2	--	1	4	9
5	1	--	3	3	10
Total cost			12469 ($M)		

Breakeven Cost: 26.32$/MWH

Here, we should mention that the average present value of the energy cost and capacity cost of the BOT as a type 5 is 19.52$/MWh and 8.15$/MWh.

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 one 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 generate more electricity, however the breakeven cost is decreased. In these two cases, the combination of other units is the same as one in the original GEP, but it is possible that change in BOT's load factor would make the combination of other units deviated.

In case 4, the BOT plant was brought forward to interval 2 from interval 3, it could be seen that a base unit (type 2) was delayed to interval 2, so the original combination of generation units was disturbed. The BOT's entry in this case increases the total cost of utility for generation addition by itself. Of course, the breakeven cost of the BOT plant is not as high as in case 2.

Furthermore, obviously, if a base type of unit is selected as a BOT to install in the original interval, its load factor would be highest, and there should be little influence 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.

It is possible to study the influence of the BOT's capacity on GEP using the approach suggested above.

VI. CONCLUSIONS

This paper presents a cost-benefit analysis of BOT plants based on long-term GEP. Because utility signs a long-term contract with a BOT plant on electric energy, price and time period, the decision should take into account BOT's influence on the GEP of the utility. In this paper, a long-term breakeven cost model for BOT is proposed, and Long-term GEP is used in this model.

Furthermore, a suitable implementation of GA method for GEP is developed that can effectively incorporate the BOT's effects.

Our suggested cost-benefit analysis model is illustrated through case studies. It has been shown that different intervals, load factor and capacity of a BOT power plant influence the GEP results differently, and sensitivity analysis on these factors should be done in the evaluation.

VII. ACKNOWLEDGMENTS

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VIII. REFERENCES

[1] C. Walker and A.J. Smith, Privatized infrastructure: the Build Operate Transfer approach, Thomas Telford, 1995.

[2] Yildiz Arikan, "Build Operate Transfer Model for New Power Plants for Turkey", Proceedings of 7th Mediterranean Electrotechonical Conference, 1994.

[3] A.K. David, "Private Investment in Power and Deviations from the Least Cost Expansion Plan", *IEE Proc.-Gener. Transm. Distrib.*, vol. 142, vo. 3, May 1995, pp. 269-276.

[4] A.K. David, "Risk Modelling in Energy Contracts between Host Utilities and BOT Plant Investors", *IEEE Trans. On Energy Conversion*, vol. 11, no. 2, June 1996, pp. 359-366.

[5] B.W. Bentley, "Integrating Non-Utility Generation into the NEPOOL Resource Planning Process", *IEEE Trans. On Power Systems*, vol.3, no. 4, November, 1988, pp. 1754-1756.

[6] W.D. Dapkus and T.R. Nowe, "Planning for New Electric Generation Technologies – A Stochastic Dynamic Programming Approach", *IEEE Trans. on Power Apparatus and Systems*, vol. PAS-103, no. 6, June, 1984, pp. 1447-1453.

[7] A.K. David and R.D. Zhao, "Integrating Expert Systems with Dynamic Programming in Generation Expansion Planning", *IEEE Trans. on Power Systems*, vol. 4, no. 3, August, 1989, pp. 1095-1101.

[8] B. Mo, et al, "Stochastic generation expansion planning by means of stochastic dynamic programming", *IEEE Trans. on Power Systems*, vol. 6, no.2, May, 1991, 662-668.

[9] R. Tanabe et al, "Flexible generation mix under multi objectives and uncertainties", *IEEE Trans. on Power Systems*, vol.8, no.2, May, 1993, pp. 581-587.

[10] J. Zhu and M.Y. Chow, "A review of emerging techniques on generation expansion planning", *IEEE Trans. on Power Systems*, Vol.12, No.4, Nov., 1997, pp.1722-1728.

[11] Y. Fukyuma and H.D. Chiang, "A parallel genetic algorithm for generation expansion planning", *IEEE Trans. on Power Systems*, vol. 11, no. 2, May 1996, pp. 955-961.

[12] Y. M. Park, J.B. Park and J.R. Won, "A hybrid generic algorithm/dynamic programming approach to optimal long-term generation expansion planning", *Electrical Power & Energy Systems*, vol. 20, no. 4, 1998, pp. 295-303.

[13] Z. Michalewicz, Genetic Algorithms + Data Structures = Evolution Programs, Springer-Verlag, 1996.

IX. BIOGRAPHIES

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