Investment Decision-Making on Renewable Energy Based on Improved Real Option Model

Wang Shicheng

School of Economy and Administration,
North China Electric Power University, Beijing 102206, China

Abstract
The huge consumption of traditional fossil energy has intensified the energy supply-demand contradiction and environmental problems. These consequences promote the urgent need for vigorous development and utilization of renewable energy, and for investment of relevant energy enterprises. Scientific and reasonable investment decision-making is the premise and guarantee that the risks in renewable energy investment can be avoided. Here we propose a real option investment and evaluation model based on back-propagation neural networks, assess the renewable energy enterprises in China, and validate the feasibility and accuracy of this model. This study underlines the decision-making for investors in the future.
Key words: BP NEURAL NETWORK, REAL OPTION, RENEWABLE ENERGY, INVESTMENT DECISION-MAKING

1. Introduction

With the intensification of energy shortage and environmental deterioration, exploitation and utilization of renewable energy becomes a necessary route that guarantees the sustainability of human society. Since renewable energy is reproducible and environmental-friendly, renewable energy enterprises are bound to be an investment hotspot in the future. However, renewable energy investment is subjected to huge risks due to high degree of uncertainty, which is decided by its long project cycle, large scale, high prophase costing, and susceptibility to policies/environment [1]. Thus, appropriate evaluation methods are necessary for reasonable assessment of values of renewable energy enterprises, providing a basis for investors in decision-making.

So far, the main evaluation methods are all based on discounted cash flow (DCF). The traditional methods are simple to use and compute, but ignore the uncertainty, flexibility, and irreversibility of renewable energy investment, thus underestimating the invested values of projects [2]. Real option method, as a mature investment decision-making method, fully considers the uncertainty and real option value contained in an investment project, and thus is widely applied in investment decision-making. As reported, the economic value of the investment in wind power energy R&D in Korea and optimal deployment timing of wind power technology were evaluated using the real option approach [3]. Wang Zhi et al. disclosed the defaults of the traditional net present value method and revealed the improvements in the real option approach, and then enumerated the types of the real option approaches and proposes the construction of the project investment decision -making models based on real option [4]. Wang Wen-ping et al. analyzed the characteristics of wind power generation project investment, proposed the ideas of introducing real option to wind power generation project investment decision, and discussed the real option model and its application in wind power generation project investment decision [5].

However, arbitrary application of a financing option pricing model will induce large errors. The Black-Scholes (B-S) model assumes the biggest potential factor that generates deviation during determination of real option values [6]. Thus, the results of the B-S model in investment decision-making are unacceptable. Regarding the limitations in the existing B-S real option investment methods, we apply back-propagation (BP) neural networks to improve the real option investment evaluation models, expecting to improve the accuracy of real option methods in assessment of renewable energy investment.

2. Improvement of real option investment evaluation models based on BP neural networks

2.1. B-S option pricing model

Based on the principle of B-S option pricing, it is assumed that the underlying asset value CVt of an enterprise obeys the following geometric Brownian motion process is shown as equation (1).

$$\frac{dCV_t}{CV_t} = \mu dt + \sigma dZ_t \tag{1}$$

where CV_t is the underlying asset value at time t; μ is the underlying expected return; σ is the instantaneous standard deviation of underlying asset value, or the value fluctuation ratio; Zt is a Wiener process, as shown in equation (2) below:

$$dZ_t = \varepsilon\sqrt{dt} \tag{2}$$

where e accords with standard normal distribution.

According to Itō's Lemma, then:

$$\frac{\partial DV_t}{\partial t} + \mu V_t \frac{\partial DV_t}{\partial t} + \frac{1}{2}\sigma^2 V_t^2 \frac{\partial^2 DV_t}{\partial V_t^2} = rDV_t \tag{3}$$

where V_t is the real option value of an enterprise at time t; r is the risk-free rate of interest.

According to the conditions upon option expiration, equation (3) should meet the boundary conditions:

$$V_T = \max(S_T - X, 0) \tag{4}$$

where T is the time a project terminates; S is the current market value of an enterprise; X is the option strike price.

According to the boundary conditions, or namely equation (4), the initial value of the differential equation above can be resolved and expressed as follows:

$$V_t = S\phi(d_1) - Xe^{-r(T-t)}(d_2) \tag{5}$$

where

$$d_1 = \frac{\ln(\frac{S}{X}) + (r + \frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{T-t}}, \quad d_2 = \frac{\ln(\frac{S}{X}) + (r - \frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{T-t}} \tag{6}$$

$\phi(\xi) = \int_{-\infty}^{\xi} \frac{1}{\sqrt{2\pi}} e^{-\frac{r^2}{2}dt}$ is a distribution function N(0, 1); r is risk-free rate of interest.

2.2. BP neural network

A BP neural network is usually composed of an input layer, a hidden layer, and an output layer. The three layers are interconnected, but the nodes between different layers are not connected. The number of nodes in the input layer is usually equal to the number of dimensions of the inputted vectors. The number of nodes in the output layer is usually the number of dimensions of the outputted vectors. The number of nodes in the hidden layer is not determined with any single criterion and usually via repeated trial and error to find out the final result. According to Kolmogorov theorem, a three-layer BP neural network containing a hidden layer (with enough hidden nodes) can approach, at any precision in a closed set, any nonlinear continuous function. Thus, a BP neural network containing one hidden layer was selected. Its topologic structure is showed in Figure1.

The input vectors of the BP neural network are assumed as x∈Rn, where x=(x_0, x_1, …, x_{n-1})T. The hidden layer has n1 neurons, whose outputs are $x \in R^{n_1}$, $x' = (x'_0, x'_1, \ldots, x'_{n-1})^T$; the output layer has m neurons, whose outputs are y∈Rm, where y=(y_0, y_1, …, y_{m-1})T. The weight from the input layer to the hidden layer is w_{ij}; the threshold is qj; the weight from the hidden layer to the output layer is w'_{jk}, the threshold is θ'_k. Thus, the neurons at each layer output:

$$\begin{cases} x'_j = f(\sum_{i=0}^{n-1} w_{ij}x_i - \theta_j), j = 0,1,\ldots,n_1 - 1 \\ y_k = f(\sum_{i=0}^{n_1-1} w'_{jk}x'_j - \theta'_k), k = 0,1,\ldots,m-1 \end{cases} \tag{7}$$

where *f*(*x*) is expressed as a Sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{8}$$

BP neural networks are a type of teacher-guided learning algorithm. It is supposed there are *n* input variables P_1, P_2, …, P_n, which are used as learning

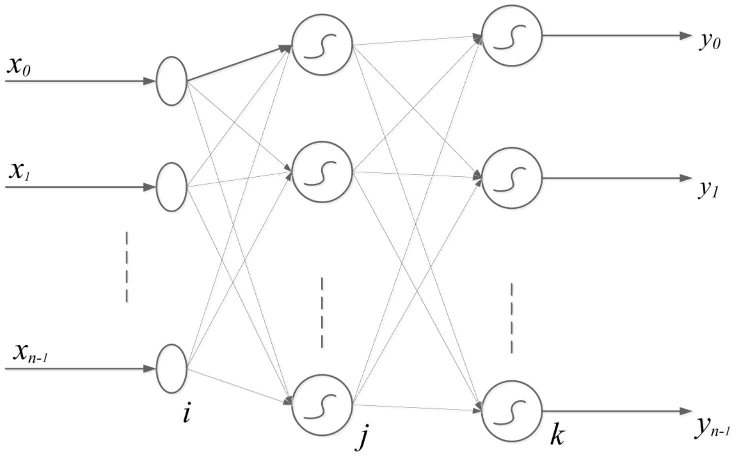

Figure 1. Topologic structure of BP neural network

samples. The n input variables correspond to teachers T1, T2, …, Tn, respectively, and to real outputs Y_1, Y_2, …, Y_n, respectively. The errors between the output values and the corresponding teachers are used to modify their connected weights and thresholds. This process is repeated such that the outputted Y is utmost approaching the demanded T. The learning process terminates when the errors are acceptable. For the n samples, a squared error function was used to compute the learning errors as follows:

$$E = \frac{1}{2}\sum_{i=1}^{n}\sum_{i=1}^{m}(T_1^i - Y_1^i) \quad (9)$$

where T_1^i is the teachers corresponding to the first group of samples; Y_1^i is the real outputs from the first group of samples. We preset a learning precision ζ. If E < ζ, the learning process terminates. The learning process of a BP neural network is illustrated in Figure2.

Moreover, a neural network with nonlinear input output relationship learning ability can learn data

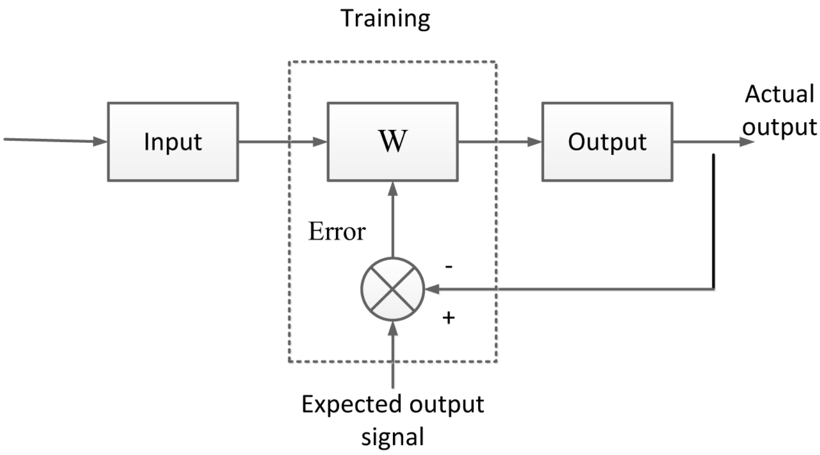

Figure 2. The learning process of a BP neural network

without special data pretreatment. However, from the perspective of improving learning efficiency and convergence speed, appropriate pretreatment can help the neural network to enhance data learning capability and prediction precision. We used a linear processing method with its transformation expressed as follows:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}, i = 1, 2, 3, \ldots \quad (10)$$

After the above processing, all data were normalized into the range 0-1, thus narrowing down the dynamic range of data identification and improving the possibility of successful prediction.

2.3. Improvement of B-S model based on BP neural networks

Generally, there are 5 main factors affecting the corporate real option value (V): Fluctuation of underlying asset σ, Present value of underlying asset S, Time of project life termination T, option strike price X, and risk-free rate of interest r. The assessment of real option value can be regarded as nonlinear mapping from inputting the 5 factors to outputting the final assessment value of this project. Thus, for a

3-layer BP neural network, the input layer contains the assessed values of these influence factors, totally 5 neurons; the number of neurons in the hidden layer can be determined as demanded. In real computation, 5 neurons in the hidden layer are determined, the output layer only has 1 neuron, one numerical value within [0, 1], indicating the assessed result of real option value. A larger value reflects a larger real option value.

2.4. Parameter estimation

(1) Present value of underlying asset (S)

For a company, its physical asset is the support of market value and the basis of future earnings. Especially for a listed company, the price of its trading can be denoted as the value of its real assets. Thus, to use the B-S model into assessment of equity value, we can substitute the present value of underlying asset by the total assets.

(2) Strike price of options (X)

Shareholders' equity is defined as the corporate value after subtracting total debts from total assets. Thus, shareholders have flexible use right, or option, to the surplus values (or enterprise assets deducted by debts), reflecting the equity has the property of option. We remark the corporate stock ownership as V, total assets as S, and select the total indebtedness on the balance sheet as the estimated value of option strike price X.

(3) Fluctuation of underlying asset σ

Under a certain amount of capital structure, an enterprise's debt value is relatively stable, so the fluctuation rate can be considered as nearly zero. Since the corporate value is equal to the sum of debt value and stock ownership value, to simplify the model, we can approximate the fluctuation rate of stock ownership value as that of corporate value. For a listed company, the fluctuation rate of corporate value can be determined directly from the fluctuation rate of its share price.

(4) Risk-free rate of interest r

Risk-free rate of interest should be estimated from the fixed stock market returns without default risks, such as rate of state treasury securities. Since the rates are different for treasury securities with different expiration dates, we selected the treasury securities with the same expiration date as the option.

(5) Time of project life termination T

Time of project life termination T was deduced from some subjective and objective factors (e.g. the enterprise's comprehensive strength, management level and core competitiveness) together with the knowledge of the enterprise's conditions. Here we estimate T through comprehensive judgment with experts and enterprises.

3. Empirical analysis

3.1. Model test

To evaluate the value of real option, a neural network needs a certain number of known samples as a training set and then undergoes big data comprehensive evaluation. Here we selected 5 listed renewable energy Chinese enterprises as a training group, and with the method for parameter estimation in Section 2.4, we estimated the values of the samples (Table 1).

Since the values of σ and *r* are both within [0, 1], they were not normalized. The other parameters were normalized. The training samples after treatment were used as input nodes in the BP network (Table 2).

The training parameters in the BP network were set as follows: 5 neurons in the hidden layer; maximum tolerable error = 0.00001; learning step size = 0.01;

Table 1. Sample values

Company	Factor					
	S	*X*	*σ*	*r*	*T*	*V*
A	3906167188.22	1857953733.14	0.3296	0.0352	10	2569448260.17
B	1542963835.72	632829378.43	0.4125	0.0324	8	1823981672.57
C	2754112872.89	907649162.88	0.3568	0.0331	7	1943571624.08
D	6257364826.46	4837259371.70	0.4037	0.0373	10	5234168215.23
E	5781249720.86	3879146280.25	0.3982	0.0325	9	4521837645.27

Table 2. Trainable samples

Company	Factor					
	S	*X*	*σ*	*r*	*T*	*V*
A	0.5013	0.2914	0.3296	0.0352	1.0000	0.2186
B	0.0000	0.0000	0.4125	0.0324	0.3333	0.0000
C	0.2569	0.0654	0.3568	0.0331	0.0000	0.0351
D	1.0000	1.0000	0.4037	0.0373	1.0000	1.0000
E	0.8990	0.7721	0.3982	0.0325	0.6667	0.7911

maximum number of learning = 500 times; adjustment parameter of weights and thresholds = 0.0005. According to Eq. (7), a pure linear transfer function (purelin) was used to compute the j-th neuron in the hidden layer, and the output was used as the input into the output layer to determine the output there.

The network training and simulation were performed on MATLAB7.0. After the 5 samples were used in network learning, we worked out a connection weight matrix between the input layer and the hidden layer as follows:

$$\begin{bmatrix} -3.5213 & 3.1953 & -2.2987 & -0.3987 & 1.4604 \\ -1.6792 & -3.5770 & 6.5030 & 1.4976 & 1.9022 \\ -2.2379 & 5.2254 & 3.9799 & 1.0117 & -1.8652 \\ -2.0351 & -5.2525 & -4.1773 & 1.1208 & -2.1766 \\ 3.2640 & -1.5205 & -0.2222 & -2.4762 & -0.0931 \end{bmatrix}$$

The threshold vectors of the input layer and the hidden layer are:

$$[\,-0.8061 \quad -0.1210 \quad -3.2121 \quad -0.4622 \quad 1.7491]^T$$

The weight matrix between the hidden layer and the output layer is:

$$[0.2509 \quad -0.1920 \quad 0.8640 \quad 0.1637 \quad -0.8128]$$

The threshold between the hidden layer and the output layer is: 0.0286.

The error variation is showed in Figure 3.

The relative errors between the simulation results obtained from the BP neural network and the real values of the sampling companies are listed in Table 3.

Table 3. Comparison between BP network training results and real data

Company	Real data	Training result	Error
A	0.2186	0.218	0.27%
B	0.0000	0.0009	-
C	0.0351	0.0355	1.23%
D	1.0000	1.0001	0.01%
E	0.7911	0.7922	0.14%

As showed in Table 3, the maximum absolute error between the training results and the real data is 1.23%, indicating the expected effect. Thus, this model can be used to assess the values of listed enterprises.

3.2. Investment decision-making

Three listed renewable energy enterprises are available for selection by investors, who can decide whether nor not to invest them by considering the current market and the operations. In this process, option to expand will occur. Thus, its current value was estimated by using a modified real option model, and the relevant parameters are listed in Table 4.

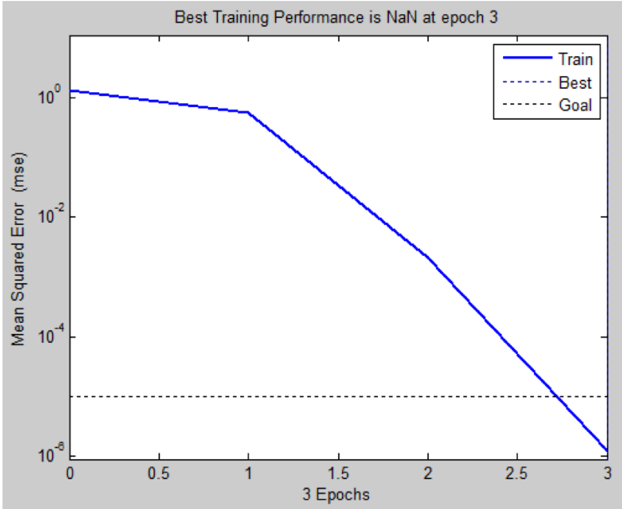

Figure 3. Network error variation curve

Table 4. Relevant parameters in investible enterprises

Company	Factor				
	S	X	σ	r	T
F	68427381.25	47692813.27	0.3366	0.0329	10
G	52971643.53	35867128.54	0.3874	0.0374	8
H	57961238.91	34869275.76	0.3661	0.0383	9

Similarly, the data were normalized and inputted into the network for simulation. The results are: VF=0.6376, VG=0.0156, VH=0.1615. Since VF >VH >VG, investors can select company F.

4. Conclusions

The high degree of uncertainty in renewable energy investment subjects investors into very large risks. Thus, appropriate evaluation methods are necessary for reasonable assessment of values of renewable energy enterprises and for helping the investors with decision-making. Here we used BP neural networks to modify the real option model and built a new value evaluation model. Five listed renewable energy Chinese enterprises were selected and used as a training set in the neural network on Matlab. The model was validated as feasible and accurate in value evaluation for renewable energy enterprises. Finally, this model was used to evaluate three renewable energy enterprises which interested the investors, providing the investors a basis for decision-making.

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Research on the Database Marketing in the Big Data Environment Based on Ensemble Learning

Yu Wang, Chengqun Yu

School of Economics and Business Administration, Chongqing University, Chongqing, 400030, China

Corresponding author is Yu Wang

Abstract
With the increasement of market competition and marketing costs, more and more companies use marketing database model to analyze and identify potential customers interested in marketing activities or products which may cause the problem of bad performance in data processing and data redundancy. In order to solve this problem, targeting customers is considered in database marketing as a classification and prediction problem in data mining under big data enviroment. Due to the variety and class imbalance of customers, a database marketing model based on supervised clustering and ensemble learning is proposed. The empirical study indicates that the proposed approach is able to improve the performance of database marketing.
Keywords: DATABASE MARKETING; CLASSIFICATION AND PREDICTION; SUPERVISED CLUSTERING; ENSEMBLE LEARNING