http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (15): 3299-3302, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.3299.3302

New Energy Project Investment Risk Computability- Optimization Model

Tongtao Ma and Cunbin Li
School of Economics and Management, North China Electric Power University,
Beijing, 102206, China

Abstract: The Chinese government is promoting energy conservation, environmental protection policies. Development of new energy generation projects has a very important significance. New energy construction projects,which has a long cycle and more technical problems, have high investment risks. Based on the characteristics of new energy projects, the model sets constraints. In order to maximize the overall revenue and reduce investment risk, this study uses CVaR theory to establish investment optimization model. And an example was given to verify the validity of the model based on the actual data. The results show that CVaR investment portfolio optimization model is able to optimize the ratio of investment and reduce investment risk of loss. There are certain practical value.

Key words: New energy, computability decision, risk optimization, energy conservation

INTRODUCTION

Energy and environmental issues are two outstanding problems which hinder the world's economic and social sustainable development. Energy conservation, green development, development and utilization of new energy sources have become the world's economic development strategy (Sarica and Or, 2007; Vaninsky, 2006). In recent years, China's new energy development has made remarkable achievements. By the end of 2011, China's new energy power generation network capacity reached 51.59 million kilowatts, generating capacity reached 93.355 billion kwh, equivalent to reduce 28.85 million tons of standard coal, the corresponding 80.2 million tons of carbon dioxide emissions, 620,000 tons of sulfur dioxide, nitrogen oxides, 27 tons. Investment in new energy fields become a hot topic in China.

As the new energy payback period is long and there are many technical problems, so there are many uncertainty in the investment. When analyzingthe power investment, investors will generally use the traditional methods of technical and economic feasibility analysis to calculate the investment yield.However, in the analysis process, investors tend to ignore the existence of the risk (Chen, 2011). In Fire, water, wind, nuclear, solar and other energy carriers there are various risks, such as financial risks, climate risks, natural risks, policy risks. These risks have a direct impact on investment income after the last power plant is built .

Risk measurement refers to the estimated and measured against the scope and extent of the likelihood of specific risks or losses (Claro and de Sousa, 2012). Only be accurately measured risk, it helps to choose an effective tool for the purpose of disposal risks and achieve the best risk management effectiveness with minimum expenses. As can be seen from the definition of risk, it is more true, accurate measurement to describe risk with the loss extent of the transaction than other indicators, such as income uncertainty, loss of uncertainties and other. The theory of VaR and CvaR of risk measurement indicators are based yields lower partial moment.The risk lower partial moment measurement theory has obvious advantages than variance theory.This theory making the "loss" as only one risk measurement factor reflects the real psychological feelings of investors (market members) to risk, in line with the behavioral science principles (Goh *et al*., 2012). In article a framework is introduced allowing us to apply nonparametric quantile regression to Value at Risk (VaR) prediction at any probability level of interest.A monotonized double kernel local linear estimator is used to estimate moderate (1%) conditional quantiles of index return distributions. For extreme (0.1%) quantiles, nonparametric quantile regression is combined with extreme value theory.Inarticle a two-stage Stochastic Integer Programming (SIP) model with a conditional value-at-risk (CvaR) constraint to incorporate risk aversion is developed. Computational results are presented that demonstrates the CVaR approach and the results are compared with a corresponding expected cost minimization approach (Lim *et al*., 2011). The SIP model with CVaR will allow acceptance of contracts at lower prices compared to an approach based on a corresponding risk-neutral model as

Corresponding Authro: Tongtao Ma, School of Economics and Management, North China Electric Power University, Beijing, 102206, China

a hedge against uncertainty and mis-specified arbitrage (Schaumburg, 2012). Foregoing considerations, based on the risk research results of the financial sector securities markets, the introduction of VaR and CVaR Risk Measurement in the electricity investment market, the pape established a electricity portfolio decision-making model.In the context of specific economic indicators, this model is able to find the best portfolio of power generation field with the maximum benefit rate target.

COMPREHENSIVE INTEGRATED MODELING APPROACH

VaR (Value at Risk) is a risk measure, refers to the maximum possible losses of a financial asset or portfolio of securities in a specific period of time in the future under normal market conditions and given confidence, called "risk value"or"VaR". Prob ($\Delta P>VaR$) = 1-β, ΔP is the portfolio loss in "Δt" holding period, VaR is the value at risk under the confidence level β (Glasserman *et al*., 2002). VaR model, the use of financial theory and mathematical statistics theory, measures the market risk of an asset or portfolio with a single indicator (VaR value).

In order to overcome the deficiencies of VaR, the researchers invented CVaR Risk Measurement theory and applied to portfolio optimization.The CVaR theory derived from VaR, also known as the average excess of loss (Mean Execs Loss), refers to the conditional mean losses exceed VaR, reflects the suffer size of average potential losses exceed VaR values, reflecting potential value-at-risk better than VaR. Figure 1 illustrates the CVaR and VaR position and relationship in the loss distribution.

PORTFOLIO OPTIMIZATION MODEL BASED ON CVAR

Due to the high risk of a variety of new energy power generation network, so when investors choose to invest in the field of power generation there are more concerns. In order to diversify risk and reduce the risk of return, investors tend to select the portfolio. The goal of the investor is in the investment and the premise of low risk, to maximize the total yield of the portfolio. Problems about optimal allocation of the total investment in the construction of a number of power generation projects, that need to be studied include: Considering the conditions of the power generation cost and market fuel prices factors such, how to optimize the total investment allocation in fire, water, wind, nuclear, solar and other power projects, with high total expected income andlow level risk after the project completion; Or in a certain level of risk (indicators), to improve the total revenue with consider raising revenue and reducing risks.

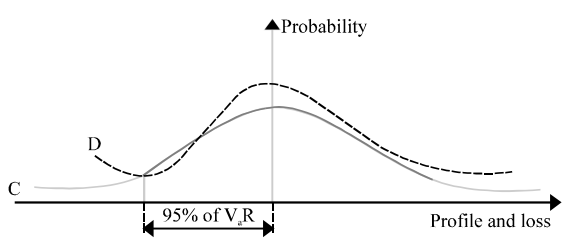

Fig. 1: Different portfolios distribution of profit and loss

In the article, the behavior that investors determine investment ratio in the field of multiple power generation, is called portfolio strategy. The study establishes a mean-CVaR optimization allocation model of the total portfolio investment,by the risk measurement indicators of CVaR (Condition value at risk), considering the risks and the expected rate of return. The application of the model can reasonably prorated the total amount of investment in several power projects, guarantee expect the premise of the yield with the minimum CVaR risk,with the premise of the minimum CVaR risk and certain expected rate. With the background of four to fire, water, wind, nuclear power generation mode, the example calculates the efficient frontier and the distribution ratio of the total investment and provides a new idea for the portfolio strategy of power suppliers.

Assume that $X^T = (x_1, x_2, ..., x_N) \in X$ is a portfolio of investors, including component x_i represents the proportion of the total amount of investment in power generation projects i. Satisfy the condition:

$$x_i \geq 0, (i=1,2,...,N), \sum_{i=1}^{N} x_i = 1 \quad (1)$$

CvaR is a consistency risk measurement indicator. Thus, the study shows that: CVaR can be applied to any distribution form of portfolio optimization. Assuming $\phi(x)$ is the risk function, R(x) is the revenue function, x is the decision vector, μ_1 is the risk factor parameters, ρ is the minimum retrun requirements, ω is the lowest risk limits, $0<\beta<1$ given. Suppose that the function φ (x) and R (x) is a function of the decision-making vector x . The following optimization problem can be shown:

$$\mathrm{Min}_x\ \phi(x_i) - \mu_1 R(x_i), x_i \in X, \mu_1 \geq 0 \quad (2)$$

$$\mathrm{Min}_x\ \phi(x_i) - \mu_1 R(x_i), \geq \rho, x_i \in X \quad (3)$$

$$\mathrm{Min}_x - R(x_i), \phi(x\, x_i) \leq \omega, x_i \in X \quad (4)$$

Assume that y_i is the i-th power project yield,then multivariate random variable $y^T = (y_1, y_2,..., y_N)$ is investors of the portfolio yiled vector. The mean vector ì of y and covariance matrix Ó are as follows:

$$\mu^T = (\mu_1, \mu_2, ..., \mu_N), \Sigma = (\sigma_{ij})_{N\times N} \tag{5}$$

Defined R (x, y) for the portfolio revenue function, the combining gain Mean E [R (x, y)] and variance σ^2[R (x, y)] are as follows:

$$E[R(x,y)] = E(rx) = x^T, \sigma^2[R(x,y)] = \sigma^2(r_x) = x^T\Sigma x \tag{6}$$

Portfolio investment loss function f (x, y) = -R (x, y), which can be given by the following equation:

$$f(x, y) = -(x_1y_1 + x_2y_2 + ... + x_ny_n) = -x^Ty \tag{7}$$

CvaR equation as follows:

$$F\beta(x,\alpha) = \alpha + \frac{1}{1-\beta}\int_{y\in R^m}[f(x,y) - \alpha] + p(y)dy \tag{8}$$

$[f (x, y)-\alpha]^+$ represents max (0, f (x, y)-α). Equation substitutions can obtain F_β (x, α) in the formas follows:

$$F\beta(x,\alpha) = \alpha + \frac{1}{1-\beta}\int_{y\in R^m}[-x^Ty - \alpha] + p(y)dy \tag{9}$$

Taken market yields y sample values $y_1, y_2, \ldots, y_q$, the estimation of the above equation is as follows:

$$F_\beta^{\sim}(x,\alpha) = \alpha + \frac{1}{q(1-\beta)}[-x^Ty^k - \alpha]^+ \tag{10}$$

A dummy variable z_k (k = 1, 2, ..., q), so $z_k = [-x^Ty^k-\alpha]^+$, k = 1, 2, ..., q and $z_k \geq 0$, $z_k \geq x^Ty^T-\alpha$. So, minimize CvaR risk investors portfolio optimization model:

$$\text{Min}(x,\alpha)\in(x,R)_\beta^{\sim}(x,\alpha,z) = \min[\alpha + 1q1 - \beta k = 1qZk \tag{11}$$

$$\text{s.t.}\, x_i \geq 0, (i=1,2,...,N), \Sigma_{i=1}^N x_i = 1 \tag{12}$$

$$x^T\mu \geq E \tag{13}$$

$$Z_k \geq 0 \tag{14}$$

$$z_k \geq -x^Ty^k-\alpha \tag{15}$$

The meaning of the constraint Eq. 26 is that a combination of expected return must be greater than the income lower bound E (0 = E = 1). The above model is to seek risk minimization under fixed expected revenue levels.

EMPIRICAL ANALYSIS

As the new energy has an important significance for environmental protection, the Chinese government encourages all kinds of new energy investment projects.In China's new energy power generation; wind and solar energy industry have a very distinct advantage. Because of large investment and high risk characteristics of wind and solar power construction, so there are most subsidies of the government for wind and solar power project investment.

The examples selected four investment field of solar energy, hydropower, wind power, biomass. Examples collected history data for the average yield and the standard deviation yield data of these areas in China from 2001 to 2010 year,which are shown in Table 1.

Normally distributed random produced a yield of 100 groups of samples: $y^K = (y_1^k, y_2^k, y_3^k, y_4^k)$, where k = 1, 2, ..., 100, confidence level β = 0.95 and β = 0.99 expected rate of return lower limit of E = 0.20 and E = 0.30. Set X_1, X_2, X_3, X_4, be the investment allocation ratio for solar energy, hydropower, wind power, biomass. Construction project.

In this model, constraint conditions are as follows.

Let M_n^k be the random investment ratio for the sample randomized. So, the total investment yield of sample randomized "E" can be rewritten as:

$$E = M_1^ky_1^k + M_2^ky_2^k + M_3^ky_3^k + M_4^ky_4^k \tag{16}$$

The total investment optimization yields "F" can be rewritten as:

$$F = y_1^kX_1^k + y_2^kX_2^k + y_3^kX_3^k + y_4^kX_4^k \tag{17}$$

Where:

$$X_1^k + X_2^k + X_2^k + X_2^k = 1, M_1^k + M_2^k + M_2^k = 1$$

Let C be the unity gain price of entire electricity market in a given period, then the units combination loss function can be rewritten as f (x, y). The purpose of optimize operation is to try to make f (x, y) reach a minimum:

Table 1: Investment income distribution of four kinds power generation

Proportion of revenue	Solar energy	Hydro power	Wind power	Biomass
Average value (μ_{yi})	0.265	0.311	0.175	0.093
Standard deviation (σ_{yi})	0.205	0.421	0.287	0.078

Table 2: Results of the investment optimize proportion

Expected revenue limit	Confidence level	X_1	X_2	X_3	X_4	VaR	CVaR
E = 0.20	β = 0.95	0.194	0.375	0.213	0.218	0.149	0.211
	β = 0.99	0.198	0.191	0.242	0.369	0.303	0.286
E = 0.30	β = 0.95	0.272	0.302	0.191	0.235	0.197	0.214
	β = 0.99	0.236	0.264	0.216	0.284	0.365	0.402

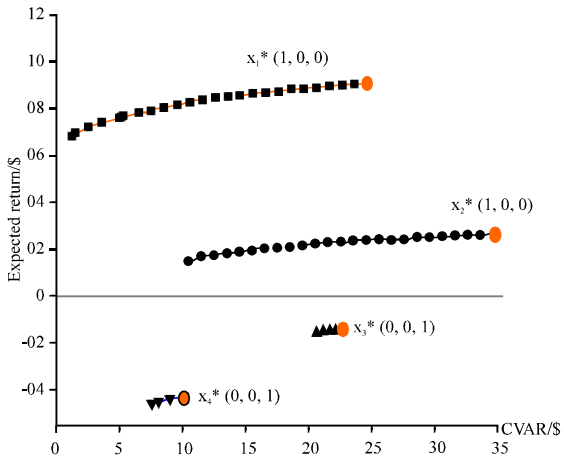

Fig. 2: Efficient frontier of mean-CVAR

$$f(x,y) = -r(x,y) = \sum_{i=1}^{N} y_i (1+b), 1 > b > 0 \quad (18)$$

Respectively using LINDO software, the optimum results are computed as shown in Table 2, including: X_1, X_2, X_3, X_4 for solar energy, hydropower, wind power, biomass construction project investment allocation ratio. The simulation results of all samples are shown in Fig. 2. It is clear that the overall yield indicators of the optimization model is better than the random sample yields. The results also proved the superiority of the model. The result (Fig. 2) clearly shows the mean-CVAR efficient frontier. Model comparison can be seen effectively that it reduces the risk and improves the expected revenue.

CONCLUSION

New energy power investment project is a new field in china. Because of the restriction factors on technology and management in the industry, there are many larger investment risks. With CVaR as risk measurement indicators, the established tender combination of mean-CVaR model CvaR risk minimization. Because the CVaR's target is to reduce below the loss and thus this model is suitable for the electricity portfolio loss rotection. It is necessary for the power industry funds with high-risk characteristics that risk indicators are introduced to the investment evaluation in the model. Based on simulation results of the example, the ratio of investment in a certain confidence level has been well optimized.The model can play purposes for overall investment risk reduction.

ACKNOWLEDGMENT

This research was supported by the National Natural Science Foundation of China: (No. 71071054, 71271084). The authors want to thank the work to this study by all anonymous reviewers.

REFERENCES

Sarica, K. and I. Or, 2007. Efficiency assessment of turkish power plants using date envelopmentanalysis. Energy, 32: 1484-1489.

Vaninsky, A., 2006. Efficiency of electric power generation in the United States: Analysis and forecast based on date envelopment analysis. J. Energy Econ., 28: 326-338.

Chen, F.Y., 2011. Analytical VaR for international portfolios with common jumps. Comput. Math. Appli., 62: 3066-3076.

Claro, J. and J.P. de Sousa, 2012. A multi objective meta heuristic for a mean-risk multi stage capacity investment problem with process flexibility. Comput. Operat. Res., 39: 838-849.

Goh, J.W., K.G. Lim, M. Sim and W. Zhang, 2012. Portfolio value-at-risk optimization for asymmetrically distributed asset returns. Eur. J. Operat. Res., 221: 397-406.

Schaumburg, J., 2012. Predicting extreme value at risk: Nonparametric quantile regression with refinements from extreme value theory. Comput. Stat. Data Anal., 56: 4081-4086.

Glasserman, P., P. Heidelberger and P. Shahabuddin, 2002. Portfolio value-at-risk with heavy-tailed risk factors. Math. Fin., 12: 239-269.

Lim, A.E.B., J.G. Shanthikumar and G.Y. Vahn, 2011. Conditional value-at-risk in portfolio optimization: Coherent but fragile. Operat. Res. Lett., 39: 163-171.