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Review

Technology portfolio modeling in hybrid environment

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Technology portfolio selection is one of the critical decision making process for any manager. This paper considers a fuzzy mixed portfolio selection with random fuzzy return and new hybrid algorithm approach for solving it. Fuzzy set theory is applied to model uncertain and flexible information. Since traditional technology evaluation methods is often unable to consider vague data gathered from environment, in this paper, the returns of each technology are assumed to be fuzzy random variables. In proposed hybrid algorithm we employ outputs of neural networks to produce initial solution for genetic algorithm and in order to reduce the computational work. Finally, the model for investment case in carwash technologies selection was applied, indicating that the proposed approach can assist decision makers in selecting suitable technology portfolios, while there is a lack of reliable project information.

Key words: Technology portfolio, fuzzy random variable, neural network, chance programming, genetic algorithm, hybrid intelligence.

INTRODUCTION

To employ the best function of resources is one of the major obligations of technology managers. This issue implicates allocating resources (asset, individuals, facilities, equipment…) to a range of various technological programs, and it includes a main question that which means should be chosen to carry out development aims (Jolly, 2003). A good technology portfolio may enable a company to promote production profitability, efficiency and capability of constant concordance, international development and appropriate competitive advantage (Cui et al., 2006). Kelly and Rice found out that firms can attract trustworthy and consistent associates by creating important technology portfolios (Kelly and Rice, 2002).

For formulating and systematizing these decisions, models of technology portfolio were designed in 1980's, with the aim of assisting technology managers in undertaking such a delicate task. The main methods of technology portfolio modeling, for certain, should take Harris et al. (1981), Foster (1981), or Little's models (1981) into account. More recent approaches, regarding the interdependences between projects, try to investigate the impacts of risk diversification (Ringuest et al., 1999) and to propose purchase strategies based on technology portfolio categorization (Hsuan, 2001), and base on qualitative approach (Akinwale and Abiola, 2007) or focus on searching for optimized portfolios, that is, suited to the new product development strategy of the firm (Balachandra, 2001).

TECHNOLOGY PORTFOLIO MODELING

Portfolio selection for strategic management is a crucial activity in many organizations, and it is concerned with a complex process that involves many decision-making situations (Lin and Hsieh, 2004). When a company intents to perform beyond its investment, it can develop its investment based on technology knowledge. Such a company can incorporate new knowledge and own unique technologies, which demands creating portfolio from technological assets (Grindley and Teece, 1997). Financial and organizational limitations can affect the technology development of a company. This problem can be observed particularly in small firms (Chan and Heide, 1993; Lerner, 1997). Maidique and Patch (1998) indicate that strategy technology is a technology portfolio that a company devises for gaining advantage in market.

Technology managers need to attract, receive and transfer technological knowledge to other sections of company, under a particular situation (Malik, 2002). In addition to above mentioned points, this technology, which plenty of studies have been undertaken on it, influences other kind of management in the company, as well. This management is called portfolio management that according to the type of technology carries out major revisions in optimal combination of assets.

One way of improving the market penetration rate of efficient technology can be generalization of portfolio concept into efficient and inefficient technologies, rather than depending on only one kind of technology. Such a conception of portfolio can contribute to diversification of risk which is associated with investments in efficient devices and equipments (Balachandra and Shekar, 2001).

So far, copious researches have been undertaken on the ground of portfolio selection. And majority of them underlie Markowitz approach and his proposed mathematical model which was based on mean-variance (Markowitz, 1952). This model by keeping its centrality has been groundwork of new models of portfolio (Ehrgott et al., 2004; Campbell et al., 1997; Elton and Gruber, 1995; Jorion, 1992). However, investigators have proposed other models for portfolio selection that some of them are: capital asset pricing model CAPM (Luenberger, 1997; Lerner, 1997), Semi-variance model (Mossin, 1966), Safety-first model (Campbell et al., 1997) and so on. The portfolio selection problem deals with how to form a satisfying portfolio. It is difficult to decide which assets should be selected because of the uncertainty on their returns (Gupta et al., 2008).

Inadequacy of Hard or Crisp mathematical models in covering uncertain, imprecise and vague states necessitates employment of fuzzy principles and method (Elton and Gruber, 1995). Particularly, incremental development of vagueness and uncertainty sources and different approaches for controlling them reveals the exigency of proposing new optimized models. The information that the decision makers obtain are usually expressed with linguistic descriptions such as high risk, low benefit or high rate of interest (Sheen, 2005) which were identified by Zade's Fuzzy theory (Zade, 1978). It was determined that insufficient knowledge around asset return and involved in the behavior of financial markets treatment can be captured by means of fuzzy quantities and/or fuzzy constraints.

Recognizing optimized point for a decision maker is difficult task and usually due to plurality of choices, it is time consuming. Inasmuch as such a decision making has to do with selection or non-selection, mostly is formulated as 0-1 function (Lin and Hsieh, 2004). Applying integer programming to risk priority reduction (Glickman, 2008) and using linear programming with infinite dimensions (Carlsson and Fuller, 2001) have been undertaken in recent years, which each of them has attempted to get the optimal answer, in a way. Therefore discussing these two states simultaneously that combine fuzzy random return and integer selection as a comprehensive model can lead to better results especially in contrast with initial models.

FUZZY RANDOM VARIABLES

In the current situations, future returns are accompanied with lots of complexities. Because of this vagueness and complicacy, predicting future returns through the method of historical data is not feasible. In order to confront this problem, researchers have suggested applying Fuzzy sets theory (Zade, 1965, 2005). But even in that case, there has also been some problems in risk calculation which is rooted in uncertainty, furthermore a lot of models have been proposed around the issue of portfolio that among them Watada (1997), Carlsson et al. (2002) and Huang's model (2007a) can be referred. However, one of the best ways in which the investors can manage uncertainty is applying random and fuzzy optimal models. In real world as well, some of the investors, faced with uncertainty, use fuzziness and randomness simultaneously (Huang, 2007b), that are indicator of random returns with fuzzy parameters and environments (Tanaka, 2000; Inuiguchi and Tanino, 2000).

Random fuzzy variables were introduced for the first time by Kwakernaak (1978, 1979). The basis of this matter in fuzzy random variable is a measurable function from a possibility space to the set of fuzzy variables.

Fuzzy random variables are indicators of fuzzy random phenomena, which are in fact future returns with fuzzy values. In other words, each random fuzzy variable $\tilde{X}$ includes at least one random variable X as origin of $\tilde{X}$. So, random fuzzy variable $\tilde{X}$ is the fuzzy consequence of uncertain design of $\Omega \tilde{\to} F(R^n)$ that $F(R^n)$ is the class of all the fuzzy numbers in R^n. Figure 1 depicts one-dimensional random fuzzy variable.

After Kwakernaak this concept was developed by researchers like Puri and Ralescu (1986), Kruse and Meyer (1987) and Liu and Liu (2003a). Liu and Liu (2003b) have presented different spectra of Expected Value Model (EVM) of fuzzy random variable, and because of the necessity of measurability and ranking of fuzzy random variables they introduced Numerical Expected Value Operator. In 2001 the concepts of optimistic and pessimistic values were proposed by Liu (2001). The capability of fuzzy random variables, will be more obvious when the probability distribution is determined. The distribution of random variable of $X \sim N(\mu, \sigma^2)$ is considered with fuzzy μ and definite σ^2. For example if $\xi \sim N(\tilde{\mu}, \sigma^2)$ and $\tilde{\mu}$ is triangular fuzzy variable $\tilde{\mu} = (a, b, c)$, then ξ is a random fuzzy

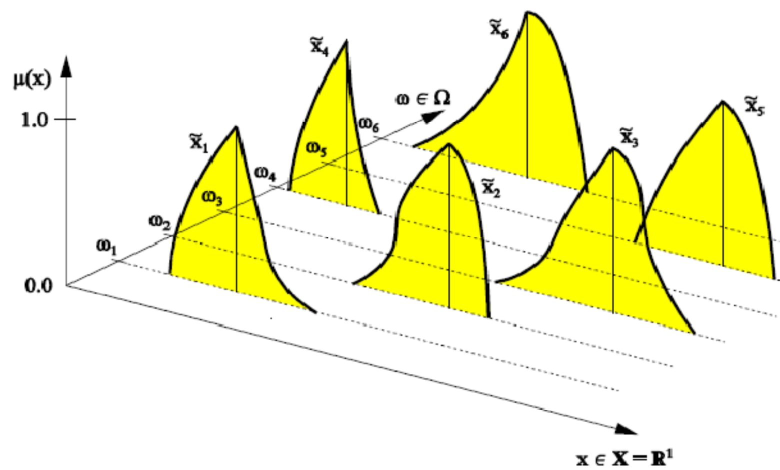

Figure 1. Quality of one-dimensional random fuzzy variable.

variable with normal distribution value (Liu, 2002).

Definition 1- A random fuzzy variable, is a function of ξ from probability space of $(\Omega, \mathrm{A}, \mathrm{P}r)$ to the set of fuzzy variables such that $Cr\{\xi(\omega \in B\ \}$ as a measurable function of ω for any Borel set B from $\Re$. For example, if $(\Omega, \mathrm{A}, \mathrm{P}r)$ is a possibility space and if $\Omega = \{\omega_1, \omega_2, ..., \omega_m\}$ and $u_1, u_2, ..., u_m$ are fuzzy variables, then function

$$\xi(w) = \begin{cases} u_1, & if \quad \omega = \omega_1 \\ u_2, & if \quad \omega = \omega_2 \\ ..... & \\ u_m, & if \quad \omega = \omega_m \end{cases} \tag{1}$$

Is clearly a random fuzzy variable (Liu and Liu, 2003 b; Liu 2006).

For example, if η is random variable defined on the probability space $(\Omega, \mathrm{A}, \mathrm{P}r)$, and $\tilde{a}$ is a fuzzy variable, then the sum $\xi = \eta + \tilde{a}$ will be a random fuzzy variable defined by

$$\xi(\omega) = \eta(\omega) + \tilde{a}, \qquad \forall \omega \in \Omega \tag{2}$$

Definition 2- Let ξ be a fuzzy variable with μ membership function μ. For any set A of real numbers, the credibility is defined as (Liu and Liu, 2002):

$$Cr\{\xi \in A\} = \frac{1}{2}(\sup_{x \in A} \mu(x) + 1 - \sup_{x \in A^c} \mu(x)) \tag{3}$$

Definition 3- Let ξ is a random fuzzy variable that is defined on incredibility space $(\Theta, P(\Theta), Cr)$ then the expected value $E(\xi)$ is defined as follows:

$$E(\xi) = \int_0^{\infty} Cr\{\theta \in \Theta | E[\xi(\theta)] \geq t\} dt - \int_{-\infty}^{0} Cr\{\theta \in \Theta | E[\xi(\theta)] \leq t\} dt \tag{4}$$

provided that at least one of the two integrals is finite (Liu and Liu, 2003c).

Portfolio model, fuzzy random variable approach

In this part the technology portfolio is formulated as optimized issue with fuzzy objectives. Portfolio selection problem involving the random fuzzy variable based on the standard asset allocation problem to maximize the total future return can be as follows (Hasuike et al., 2009):

$$\begin{aligned} &Maximize \qquad z = \sum_{i \in N} \tilde{\bar{r}}_i x_i \\ &Minimise \qquad Var(\sum_{i=1}^{n} \tilde{\bar{r}}_i x_i) \\ &S.t: \qquad \sum_{i \in N} \sum_{j \in N} a_{ij} x_{ij} \leq b \end{aligned} \tag{5}$$

that $a_{ij}, b \in R$ are real coefficients, and $\bar{\bar{r}}_{ij}$ is the average of the future return rate of technology i, and they are in the form of fuzzy random variables, it means that $\bar{\bar{r}}_{ij} \in F(R)$. Also σ_{ij} is the common covariance which is considered for risk reduction in portfolio models. To date, different methods for integrating the twofold objectives have been devised. The objective function of the above model can be revised in the form of integrating risk reduction and the return average increase. For undertaking this task, assume that $\lambda \in [0,1]$ is the parameter for risk aversion. So it can be written:

And in the case that the values of the variables are in the form of integer, we have:

$$
\begin{aligned}
&Minimise \quad \lambda\left[\sum_{i=1}^{n}\sum_{j=1}^{n} x_i \sigma_{ij} x_j\right] + (1-\lambda)\left[-\sum_{i=1}^{n}\tilde{\mu}_{ri} x_i\right] \\
&S.t: \quad \sum_{i\in N}\sum_{j\in N} a_{ij}x_{ij} \le b \\
&\quad \sum_{i=1}^{n} x_i = k \\
&\quad ly_i \le x_i \le uy_i \\
&\quad y_i \in \{0,1\}
\end{aligned} \tag{6}
$$

Where $\lambda = 0$ represents the state of the maximizing the return and it is the optimal point with the highest return mean. Any value between (0 and 1) is the representative of the exchange between the return mean and variance that will have an answer between the two ends of the problem when $\lambda = 0$ and $\lambda = 1$.
k is the representative of the limitation of the technologies number.
And u, l are also the representatives of the high and low limits considered by the investor to purchase the type i technology.

One of the dimensions of the twofold models of portfolio is decreasing the risk, which is fulfilled by minimizing the variance. In this study, by considering the point that the returns of technologies are as random fuzzy LR variables, the covariance of these variables equals (Nather, 1997; Korner, 1997):

$$
\begin{aligned}
Cov[X,Y] &= Cov[m_x, m_y] + a_{l_2}[Cov(l_X, l_Y) + Cov(r_X, r_Y)] \\
&\quad -2a_{l_1}[Cov(m_x, r_Y - l_Y + Cov(m_Y, r_X - l_X)
\end{aligned} \tag{7}
$$

That l, m, r are the triangular fuzzy numbers. Supposing that the random LR variables are symmetrical, we have:

$$
\begin{aligned}
Cov[X,Y] &= Cov[m_x, m_y] + a_{l_2}[Cov(l_X, l_Y) + Cov(r_X, r_Y)] \\
&\quad -2a_{l_1}[Cov(m_x, l_Y) + Cov(m_Y, l_X)
\end{aligned} \tag{8}
$$

Regarding the independence assumption of l, m, r it can be written:

$$Var(X) = Var(m) + \frac{1}{6}Var(l) + \frac{1}{6}Var(r) \tag{9}$$

And

$$Cov(X,Y) = Cov(m_X, m_Y) + \frac{1}{3}Cov(l_X, l_Y) \tag{10}$$

Regarding the point that both left and right ranges are equal when the random variables are normal, it can be written:

$$Var[\tilde{r}] = \sum_{i=1}^{n}\sum_{j=1}^{n} X_i X_j [Cov(\tilde{r}_i, \tilde{r}_j) + \frac{1}{3}Cov(\tilde{l}_i, \tilde{l}_j)] \tag{11}$$

Where $\tilde{r}_i$, $\tilde{r}_j$, the returns of variables i and j, and $\tilde{l}_i$, $\tilde{l}_j$ are indicators of their ranges.

The type of above model cannot be solving with common methods so we employ Max-Min approach and nonlinear programming methods. The nonlinear algorithm that would be considered in this research is hybrid algorithm. Nonlinear optimization will employ hybrid intelligence algorithm that use neural networks outputs as the input chromosomes (Huang, 2007b) and Max-Min approximation can be based on Lai and Hwang (1992).

PROPOSED MODEL

The objective function of the problem

In the mean and variance model of Markowitz (1952, 1959), the returns have been considered as random variables and it has been supposed that the investors are aiming at striking balance between maximizing the return and minimizing the risk of investment. Thus, the returns with the mean, and the risk with the variance portfolio became quantitative.

The random fuzzy variables are one of the best possible ways to encounter the simultaneous random and fuzzy uncertainty (Li and Xu; 2009). If we suppose that the return of technology i is a fuzzy random variable, its membership function can be displayed in the simple triplet (l, m, u) form, as it is shown in the following:

$$
\mu = \begin{cases} \dfrac{x-l}{m-l} & l \le x \le m \\ \dfrac{x-u}{m-u} & m \le x \le u \\ 0 & otherwise \end{cases} \tag{12}
$$

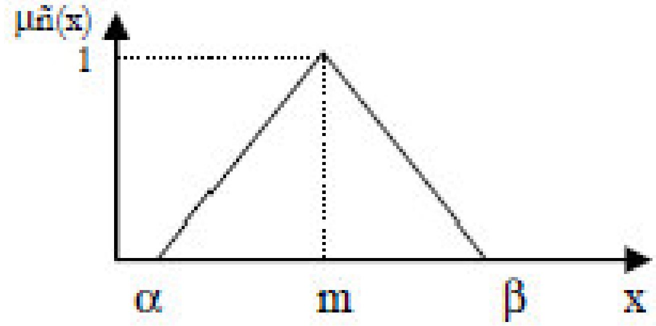

Figure 2. Triangular fuzzy numbers.

The reason of using triangular fuzzy numbers for the fuzzy parameters is the augmentation of calculating efficiency (Klir and Yuan, 1995) (Figure 2).

The return rate of each technology is in the form of fuzzy triangular numbers as: $r_i = (m_i - \alpha_i, m_i, m_i + \beta_i)$ in which m_i, is the random variable with normal distribution $m_i \sim N(E(m_i), \sigma_i^2)$, α_i and β_i are also left and right spreads, respectively.

The objective function of the problem can be reflected in the form of defining variables of the future incomes as random fuzzy and reducing risk.

$$Max \sum_{i=1}^{n} \tilde{\tilde{r}}_i X_i \tag{13}$$

$$Min \;\; Var(\sum_{i=1}^{n} \tilde{\tilde{r}}_i X_i) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} x_i x_j \tag{14}$$

where: $\tilde{\tilde{r}}_i$: The mean of the future monthly income of technology i which is in random fuzzy variable form. σ_{ij} : The common covariance

$$X_i = \begin{cases} 0 & if \quad thechnology \quad i \quad is \quad purchased \\ 1 & otherwise \end{cases}$$

We can revise the above objective function in the following way:

Above nonlinear function (13), with replaced expected value of distribution, can be rewritten as:

$$Max \sum_{i=1}^{n} E(\tilde{r}_i X_i) \tag{15}$$

Because r is the random with normal distribution, we can use normal mean for expected value. And also can be rewritten risk objective function as a separate constraint:

$$Ch\{\sum \tilde{r}_i x_i \le b_i\}(\gamma) \ge 1 - \alpha_i \tag{16}$$

Where b_i represents investigator target return, α_i is the predetermined confidence level and γ is the pessimistic return from technology i.

And also, because the chance of a random fuzzy event characterized by $f(\xi) \ge 0$ is a function from (0, 1] to [0, 1], defined as (Liu, 2002)

$$Ch\{f(\xi) \ge 0\}(\gamma) = \sup_{Cr\{A\} \ge \gamma} \inf_{\theta \in A} \Pr\{f(\xi(\theta)) \ge 0\} \tag{17}$$

thus,

$$Ch\{f(\xi) \ge r\}(\gamma) = \Pr\{f(\xi(\theta)) \ge r\} \tag{18}$$

That for any specific r value can be calculated as follow:

$$Ch\{\sum \tilde{r}_i x_i \le b_i\} \ge 1 - \alpha_i = \Pr\{b_i - (\sum_{i=1}^{n} \tilde{r}_i x_i) \ge r_0\} \le \alpha_0 \tag{19}$$

The constraints of the problem

a) The starting up constraint: this constraint is related to the costs of starting up the technology. The starting-up costs should not be higher than the initial budget of investment, that:

$$\sum_{i=1}^{n} S_i X_i \le BI \tag{20}$$

S_i, is the required budget for purchasing and starting up technology i, and

BI, is the initial budget of investment.

b) The workforce constraint: this limitation represents individuals that are skilled in working with technology i and are needed and should be in access. By taking into consideration that determining the exact number of qualified individuals in work market is not possible and judging about the amount of their skill and their number involves some vagueness, the fuzzy numbers' set is used for expressing the judgment of experts.

$$\sum_{i=1}^{n} \tilde{p}_i X_i \le \tilde{P}_i \tag{21}$$

$\tilde{p}_i$: The number of required qualified individuals for working with technology i.

$\tilde{P}_i$: The number of available qualified individuals for working with technology i.

c) The return constraint: The return rate of any technology for fulfilling investors' objectives should be higher than the investors' expected return rate for Technology i in a span of time. The expected rate is taken into account as fuzzy, inasmuch as the vagueness and uncertainty of the rate, in order to make every specified ranges of return, for each technology, possible to investigation. That:

$$\sum_{i=1}^{n} \tilde{r}_i X_i \geq \tilde{R}_{\exp_i} \qquad (22)$$

$\tilde{r}_i$ is the future return rate of Technology i

$\tilde{R}_{\exp i}$ is the future expected rate for Technology i

d) The volume constraint: this limitation is the representative of total number of possible technologies.

$$\sum_{i=1}^{n} X_i = k \qquad (23)$$

e) The variables constraint.

$$ly \leq x_i \leq uy \quad ;\text{int}\,eger \quad i = 1,2,...,n$$
$$y \in \{0,1\} \qquad (24)$$

l and u are lower and upper number of one technology type in portfolio, respectively.

Now we can formulate the model as:

$$\begin{aligned}
&Max \quad f\\
&st:\\
&\Pr\{\sum_{i=1}^{n} \tilde{r}_i x_i \geq f\} \geq \beta_0\\
&\Pr\{b_i - (\sum_{i=1}^{n} \tilde{r}_i x_i) \geq r_0\} \geq \alpha_0\\
&\sum_{i=1}^{n} S_i x_i \leq BI\\
&\sum_{i=1}^{n} \tilde{p}_i x_i \leq \tilde{P}_i\\
&\sum_{i=1}^{n} \tilde{r}_i x_i \geq \tilde{R}_{\exp_i}\\
&\sum_{i=1}^{n} x_i = k\\
&ly_i \leq x_i \leq uy_i\\
&y_i \in \{0,1\}\\
&x_i ;\text{int}\,eger \quad i = 1,2,...,n
\end{aligned}$$

The performance of the model

In order to test the model, investment in starting up a huge carwash was studied. Various and related technologies in this area included different sorts of fully automatic, half automatic, and manual advanced machines which were in different groups such as washing passenger cars, trucks, tankers, trains, and water jets, floor washers, chair washers, polishers, … and in various spectra of models and facilities. Since it was not possible to mention the commercial names, abbreviator signs were used for them.

First, the rate of the expected return of each technology and the right and left limits have been calculated. Calculation of the right and left sides' values, the vector of the expected return rate, and the matrix of covariance has been made by employing historical data and experts' (the owners of car washes and sellers) ideas. For gathering this data, at first the historical data of thirteen models of car wash equipments during the past 12 months in the years 2009-2010 have been collected and used for approximating the return rate of technologies and covariance matrix $V = (Cov(a_i, a_j))_{n\times n}$. Subsequently, the experts and active individuals in this area were asked to state their own estimation of the rate of α_i and β_i. The mean of these estimates were considered as right and left limits and the return rate of fuzzy random variable of Technology i is $E(r_i) = (E(m_i) - \alpha_i, E(m_i), E(m_i) + \beta_i)$.

The number of technologies considered by the investor is aggregately four $(k = 4)$ machines, and maximum number of technology i and personnel, is 2 Unit, 3 people, respectively. Also the initial budget of investment is 400 million. Expected rate $(R_{\exp})$ has obtained 0.85 with 0.3 and 0.15 upper and lower spreads respectively from questioners.

HYBRID INTELLIGENT SYSTEM

Since it is difficult to find the optimal solution of the proposed model (Chow, Denning; 1994) in traditional ways, we use linear and nonlinear (hybrid) approximation methods simultaneously. We can use the technique of simulation (Colubi, 2002) and genetic algorithm (Holland, 1975) based on random fuzzy simulation to help find the optimal solution with hybrid algorithm. When random fuzzy simulation is integrated into GA, the algorithm will take a fairly long time to find the optimal solution. In order to lessen the computational work, we employ neural networks (NNs). NNs are famous for approximating any nonlinear continuous functions over a closed bounded set (Huang, 2007b). An ANN creates a model of neurons and

Table 1. Comparisons of object values by hybrid intelligent system.

Population size	P_m	Crossover function	f	X
20	0.2	0.8	0.685879	4,4,7,13
20	0.2	0.5	0.452937	1,4,12,13
20	0.3	0.8	0.5503178	4,4,10,13
20	0.3	0.5	0.8940088	7,7,10,13
30	0.2	0.8	0.9294400	4,5,12,13
30	0.2	0.5	0.92452	5,7,12,13
30	0.3	0.8	0.946780	3,4,5,13
30	0.3	0.5	0.9543	3,4,10,12

the connections between them, and trains it to associate output neurons with input neurons. The network ‘‘learns’’ by adjusting the interconnections (called weights) between layers. When the network is adequately trained, it is able to generate relevant output for a set of input data (Mirbagheri, 2010).

In order of neural network modeling, we use one input layer, one hidden layer (with 13 neurons) and two neurons as output layer. In this research, one training data set for uncertain objective function employed and for training theses data, back propagation algorithm investigated. And also, logistic sigmoid function used in hidden layer.

Also, for running genetic algorithm we define an integer pop-size = 30 as the number of chromosomes and initialize pop-size chromosomes randomly to produce feasible chromosomes explicitly. Expected values and chances were calculated by them. The probability of crossover and probability of mutation are $p_c = 0.5$, $p_m = 0.3$ respectively.

The hybrid intelligent algorithm was described as follows:

Step 1. Generate training input-output data for uncertain functions like

$$U_1 = \max\{\bar{f} \mid \Pr\{\sum_{i=1}^{n} \tilde{r}_i x_i \geq \bar{f}\} \geq \beta_0\}$$

$$U_2 = \Pr\{b_i - (\sum_{i=1}^{n} \tilde{r}_i x_i) \geq r_0\}$$

$$U_3 = E[f(x), \xi]$$

by the random fuzzy simulation.

Step 2. Train a neural network to approximate the uncertain functions according to the generated training input-output data.

Step 3. Initialize *pop size* chromosomes whose feasibility may be checked by the trained neural network.

Step 4. Update the chromosomes by crossover and mutation operations.

Step 5. Calculate the objective values for all chromosomes by the trained neural network.

Step 6. Compute the fitness of each chromosome according to the objective values.

Step 7. Select the chromosomes by spinning the roulette wheel according to the different fitness values.

Step 8. Repeat the fourth to seventh steps for a given number of cycles.

Step 9. Report the best chromosome as the optimal solution of technology portfolio selection problem.

A run of the hybrid intelligent algorithm (1000 cycles in random fuzzy simulation, 500 training data in NN, and 500 generations in GA) shows the optimal solution as Table 1, whose objective value $\bar{f} = 0.954$ is highest achieved goal value.

CONCLUSION

Because the returns of each technology in the future cannot be represented with historical data especially in the absence of enough data situation, in this paper, we have considered technology portfolio selection in hybrid environment with random fuzzy returns and linear and fuzzy constraints to set output as integer values. To solving randomness and fuzziness simultaneously, a hybrid intelligent algorithm is provided to estimate objective function with combinational constraints. Expected values and the chance constraints were calculated with neural network and feasible output employed in hybrid genetic algorithm. An example is given to illustrate the proposed fuzzy random project portfolio selection using real data from Carwash Industry; results showed high fitness of model (Table 1).

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