Fuzzy Random Dependent-Chance Programming Models of Loan Portfolio

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***Abstract*—The environment of loan in bank is very complex, there are not only random factors but also fuzzy factors, so the return rates of loan often have fuzzy random characteristic. Mean chance is a measure of fuzzy random variable. This paper proposes two fuzzy random dependent-chance programming models of loan portfolio, one is minimize the mean chance of a bad outcome under the certain expected return rate, one is maximize the mean chance of the prospective return rate under the certain expected return rate. Hybrid intelligent algorithms are employed to solve the models. Finally, two numerical examples are given to show the validity and feasibility of the models and algorithms.**

***Index Terms*—dependent-chance programming, loan portfolio, mean chance, fuzzy random**

I. INTRODUCTION

In order to distribute risk, the bank puts loan in the different projects, which is loan portfolio. Essentially, it is portfolio selection. Loan portfolio is that the bank should decide how to allocate the certain capital in proportion so as to obtain the maximal return rates and the minimal risk. Since Markowitz[1] initialized the mean-variance model of portfolio selection, many scholars propose many different methods to solve portfolio problem. Tang[2] gave a kind of probability criterion portfolio investment model, in the model, the objective is to maximize the probability of the prospective return rare. Under the constraint of certain returen rate, Sheedy[3] establishes the asset allocation decision model when the risk changes. Ning[4] gives chance programming model of loan portfolio when the return rate is fuzzy. Dietsch and Petey[27] proposed a internal credit risks model about SME loan. Huang[16] measured portfolio risk by the variance based on credibility and proposed two new credibility-based fuzzy mean-variance models. Tanaka and Guo[15] quantified mean and variance of a portfolio through fuzzy probability and possibility distributions. These models' objective is mainly maximize the return rates under the constraint of certain risk, or minimize the risk under the constraint of certain return rate. Risk is primarily mathematically defined in three ways: variance, semivariance and a probability of a bad outcome. Based on Markowitz's mean-variance model, a large numbe of extensions have been proposed[5,6,7,8]. Semivariance is another measure of risk proposed by Markowitz[9], semivariance is an important improvement of variance because it only measures the investment return below the expected value. Many models have been built to minimize the semivariance from different angles[10,11],. The third popular definition of risk is a probability of a bad outcome initially by Roy[12]. Much research has been undertaken to find ways of minimizing the probability of the bad outcome[13,14].

However, the above studies mainly focused in two directions: stochastic environment and fuzzy environment. But the investment environment is so complex, sometimes we have to deal with the uncertainty of both fuzziness and randomness simultaneously. For example, the loan return rate can be regarded to be triangle fuzzy variable $(\rho - 0.1, \rho, \rho + 0.1)$, and ρ is random variable. Thus we have to face "fuzzy return rates with random parameters". To deal with this type of uncertainty, this paper proposes that return rates be regarded as fuzzy random variable. Huang[23] gave a new optimal model of portfolio selection with random fuzzy returns, the paper proposed the primitive chance measure of risk, but the primitive chance measure only measures the maximum possibility of a random fuzzy or fuzzy random event occurs under a given probability level, and she did not research optimal model in fuzzy random environment. So in this paper, we consider the loan portfolio problem in fuzzy random environment, and because the mean chance measures the mean or expected possibility of the fuzzy random event, it can show the possibility of the fuzzy random event more extensive than primitive chance, so we use the mean chance of a bad outcome to measure the risk. Base on mean chance, this paper proposes two new dependent-chance programming models, one is minimize the mean chance of a bad outcome under the certain expected return rate, another is maximize the mean chance of the prospective return rate under the certain expected return rate, and designs hybrid intelligent algorithms to solve the models.

The rest of the paper is organized as follows. For better understanding of the paper, some basic knowledge about fuzzy random variables is introduced in section 2. In section 3, we propose two new dependent-chance programming models based on mean chance. In order to give a general algorithm for the models, hybrid intelligent

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algorithms integrating fuzzy random simulation, neural network and genetic algorithm are designed in section 4. In section 5, two numerical examples are given to show the new models and the efficiency of the algorithms. Finally, a brief summary of this paper is given in section 6.

II PRELIMINARIES

Fuzzy random variable is a math description of fuzzy random phenomenon, it has different math definings, it was first introduced by Kwakernaak[17,18], then Puri and Ralescu[19], Liu and Liu[20] gave the defferent measure of fuzzy random variable. And according to the need of different theory, many scholars gave the different mathematical definitions and different measures of fuzzy random variable. In this paper, we use the definitions of fuzzy random variable given by Liu and Liu[20]. Roughly speaking, a fuzzy random variable is a measurable function from a probability space to a collection of fuzzy variables. The primitive chance measure, mean chance measure of a fuzzy random event have been defined by Liu[21], and the concepts of expected value operator of fuzzy random variable was also presented by Liu[24]. Fuzzy random theory play an important role in solving optimization problems involving both fuzziness and randomness. In this paper, we will employ the fuzzy random theory to solve the loan portfolio problem in a fuzzy random environment.

In order to better understanding this paper, some concepts of probability, possibility, necessity and credibility measure were first briefly reviewed, and then we introduce the concept of a fuzzy random variable and the expected value, primitive chance measure, mean chance measure of a fuzzy random variable.

Definition 1 Let Ω be a nonempty set, and $\mathcal{A}$ a $\sigma - a\lg ebm$ of subsets of Ω. The set function Pr is called a probability measure if

(1) $\Pr\{\Omega\} = 1$;

(2) $\Pr\{A\} \geq 0$ for any $A \in \mathcal{A}$;

(3) for any countable sequence of mutually disjoint events $\{A_i\}_{i=1}^{\infty} = \sum_{i=1}^{\infty} \Pr\{A_i\}$.

Then the triplet $(\Omega, \mathcal{A}, \Pr)$ is called a probability space.

Definition 2 Let Θ be a nonempty set, and $\mathrm{P}(\Theta)$ the power set of Θ, if for each $A \in \mathrm{P}(\Theta)$, there is a nonnegative number $\mathrm{Pos}(A)$, called possibility, such that

(1) $\mathrm{Pos}\{\phi\} = 0$, $\mathrm{Pos}\{\Theta\} = 1$;

(2) $\mathrm{Pos}\{\bigcup_i A_i\} = \sup_i \mathrm{Pos}\{A_i\}$ for any arbitrary collection $\{A_i\}$ in $\mathrm{P}(\Theta)$.

Then the triplet $(\Theta, \mathrm{P}(\Theta), \mathrm{Pos})$ is called a possibility space.

Definition 3 Let ξ be a fuzzy variable on a possibility space $(\Theta, \mathrm{P}(\Theta), \mathrm{Pos})$ with membership function μ, and r a real number. The possibility, necessity, and credibility of a fuzzy event, characterized by $\xi \leq r$, is defined by

$$\mathrm{Pos}\{\xi \leq r\} = \sup_{u \leq r} \mu(u),$$

$$\mathrm{Nec}\{\xi \leq r\} = 1 - \mathrm{Pos}\{\xi > r\} = 1 - \sup_{u > r} \mu(u),$$

$$\mathrm{Cr}\{\xi \leq r\} = \frac{1}{2}(\mathrm{Pos}\{\xi \leq r\} + \mathrm{Nec}\{\xi \leq r\}).$$

The expected value of a fuzzy variable is defined by

$$E[\xi] = \int_0^{\infty} Cr\{\xi \geq r\}dr - \int_{-\infty}^{0} Cr\{\xi \leq r\}dr \ .$$

In order to avoid the action of $\infty - \infty$, at least one of the two integrals of above formula is finite.

Definition 4 （Liu and Liu[20]）A fuzzy random variable ξ is a measurable function from a probability space $(\Omega, \mathcal{A}, \Pr)$ to a collection of fuzzy variables.

Example 1 Let $\xi = (\rho - 0.5, \rho, \rho + 1.5)$, and $\rho \sim \exp(1)$, then ξ is called a fuzzy random variable.

Example 2 Let $(\Omega, \mathcal{A}, \Pr)$ be probability space, if $\Omega = (\omega_1, \omega_2, \cdots, \omega_m)$ and $\eta_1, \eta_2, \cdots, \eta_m$ are fuzzy variables. Then the function

$$\xi(\omega) = \begin{cases} \eta_1, & if\ \omega = \omega_1 \\ \eta_2 & if\ \omega = \omega_2 \\ \cdots & \cdots \\ \eta_m & if\ \omega = \omega_m \end{cases}$$

is a fuzzy random variable.

Definition 5 (Liu and Liu[20]） Let ξ be a fuzzy random variable defined in probability space $(\Omega, \mathcal{A}, \Pr)$, The expected value of ξ is defined by

$$E[\xi] = \int_0^{\infty} \Pr\{\omega \in \Omega \mid E[\xi(\omega)] \geq r\}dr$$

$$- \int_{-\infty}^{0} \Pr\{\omega \in \Omega \mid E[\xi(\omega)] \leq r\}dr$$

In order to avoid the action of $\infty - \infty$, at least one of the two integrals of above formula is finite.

Definition 6 (Liu[21], Gao and Liu[22]) Let $\xi = (\xi_1, \xi_2, \cdots, \xi_n)$ be fuzzy random vector that is defined in probability space $(\Omega, \mathcal{A}, \Pr)$, $f : R^n \to R^m$ is measurable function. Then the primitive chance of a fuzzy random event characterized by $f(\xi) \leq 0$ is a function from (0,1] to [0,1], defined as

$$\mathrm{Ch}\{f(\xi) \leq 0\}(\alpha)$$

$$= \sup\{\beta \mid \Pr\{\omega \in \Omega \mid \mathrm{Cr}\{f(\xi(\omega)) \leq 0\} \geq \beta\} \geq \alpha$$

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We call $\text{Ch}\{f(\xi)\le 0\}(\alpha)$ α primitive chance of the fuzzy random event $f(\xi)\le 0$.

Theorem 1 (Gao and Liu[22]) Let ξ be fuzzy random vector that is defined in probability space $(\Omega,\mathcal{A},\Pr)$, $f:R^n\to R^m$ is measurable function, then $\text{Ch}\{f(\xi)\le 0\}(\alpha)$ is a decreasing function of α.

Definition 7 (Liu[24]) Let $\xi=(\xi_1,\xi_2,\cdots,\xi_n)$ be fuzzy random vector that is defined in probability space $(\Omega,\mathcal{A},\Pr)$, $f:R^n\to R^m$ is measurable function. Then the mean chance of a fuzzy random event characterized by $f(\xi)\le 0$ is defined as

$$Ch^a\{f(\xi)\le 0\}=\int_0^1 Ch\{f(\xi)\le 0\}(\alpha)d\alpha$$

The value of the primitive chance at α measures the maximum possibility of a fuzzy random event occurs under a given probability level α, while the mean chance measures the mean or expected possibility of the fuzzy random event[26]. The geometric meaning of mean chance is shown in Fig.1, mean chance equals to the area encircled by the curve and the coordinate axis.

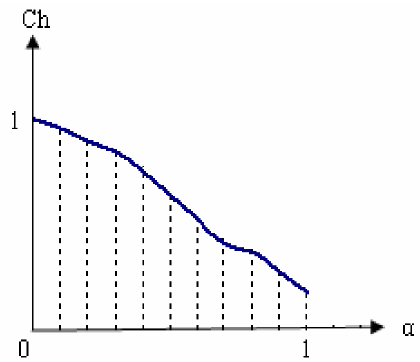

Fig.1 Geometric meaning of mean chance

III TWO NEW DEPENDENT-CHANCE PROGRAMMING MODELS OF LOAN PORTFOLIO

Supposing the bank will loan for n projects, let x_i represent the loan proportion for the ith project, $X=(x_1,x_2,\cdots,x_n)$ is decision vector, $\xi=(\xi_1,\xi_2,\cdots,\xi_n)$ is the vector that is composed of return rates of n kinds of loan, ξ_i represents the ith return rate, it is a fuzzy random variable, R_0 is the preset bad outcome return rate. In order to avoid risk, we can minimize the mean chance of the return rates less than the preset bad outcome R_0 under the constraint of expected return rates no less than μ, so the following model can be given:

$$\begin{cases}\min Ch^a(\sum_{i=1}^n x_i\xi_i\le R_0)\\ s.t.\\ \quad E[\sum_{i=1}^n x_i\xi_i]\ge\mu\\ \quad \sum_{i=1}^n x_i=1\\ \quad x_i\ge 0,\ i=1,2,\cdots,n\end{cases}\qquad(1)$$

If we set the prospective return rate is R_1, the target is to maximize the mean chance of the return rates more than R_1 under the constraint of expected return rates no less than μ, we can get the following model:

$$\begin{cases}\max Ch^a(\sum_{i=1}^n x_i\xi_i\ge R_1)\\ s.t.\\ \quad E[\sum_{i=1}^n x_i\xi_i]\ge\mu\\ \quad \sum_{i=1}^n x_i=1\\ \quad x_i\ge 0,\ i=1,2,\cdots,n\end{cases}\qquad(2)$$

Because the return rates of loan are fuzzy random variables, it is hard to find out crisp equivalents of the above models, so hybrid intelligent algorithms are employed to solve the models.

Ⅳ HYBRID INTELLIGENT ALGORITHM

Now we mainly take model(1) for example to illustrate the solving process. Since return rates are fuzzy random variables, it is difficult to solve model(1) in traditional ways. To provide a general solution to the model (1), we design a hybrid intelligent algorithm integrating genetic algorithm(GA), fuzzy random simulation and neural network(NN). Fuzzy random simulation is applied to compute the objective values of mean chance $Ch^a(\sum_{i=1}^n x_i\xi_i\le R_0)$ and the expected return rate $E[\sum_{i=1}^n x_i\xi_i]$, GA is employed to find the optimal solution. In order to reduce the computational work, neural network is trained to approximate the objective values of mean chance $Ch^a(\sum_{i=1}^n x_i\xi_i\le R_0)$ and the expected return rates $E[\sum_{i=1}^n x_i\xi_i]$.

A Fuzzy random simulation:

We should utilize fuzzy random simulation to estimate the uncertain functions[24]:

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$$U_1 : x \to Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$$

$$U_2 : x \to E[\sum_{i=1}^{n} x_i\xi_i]$$

Fuzzy random simulation for $U_1(x)$: we first compute primitive chance $Ch(\sum_{i=1}^{n} x_i\xi_i \le R_0)(\alpha)$ through step 1 to step 4.

Step1 Generate $\omega_1, \omega_2, \ldots, \omega_m$ from Ω according to the probability measure $\Pr$.

Step 2 Comput the credibility $\beta_k = Cr\{\sum_{i=1}^{n} x_i\xi_i(\omega_k) \le R_0\}$, $k = 1,2,\ldots,m$, respectively, by fuzzy simulation.

Step 3 Set m' as the integer part of αm.

Step 4 Return the m'th largest element in sequence $\{\beta_1, \beta_2, \ldots, \beta_m\}$.

Let α change from 0 to 1, then $Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$ can be computed through the following formula

$$Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0) = \int_0^1 Ch(\sum_{i=1}^{n} x_i\xi_i \le R_0)(\alpha)d\alpha$$

In the above step 2, the fuzzy simulation process of $Cr\{f(\xi) \le R_0\}$ is described as follows:

Generate θ_k in Θ evenly and make $Pos\{\theta_k\} \ge \varepsilon$, let $v_k = Pos\{\theta_k\}$, $k = 1,2,\ldots,N$, ε is a small number enough, the credibility of $Cr\{f(\xi) \le R_0\}$ can be estimated by the following formula

$$L = \frac{1}{2}(\max_{1\le k\le N}\{v_k \mid f(\xi(\theta_k)) \le R_0\} + \min_{1\le k\prec N}\{1 - v_k \mid f(\xi(\theta_k)) > R_0\})$$

, then L is the fuzzy simulation value of $Cr\{f(\xi) \le R_0\}$.

Fuzzy random simulation for $U_2(x)$ is described as follows:

Step 1 Set $e = 0$.

Step 2 Generate ω from Ω according to the probability measure $\Pr$.

Step 3 $e \leftarrow e + E[\sum_{i=1}^{n} x_i\xi_i(\omega)]$, $E[\sum_{i=1}^{n} x_i\xi_i(\omega)]$ can be computed by fuzzy simulation.

Step 4 Repeat the second to third steps for N times.

Step 5 $E[\sum_{i=1}^{n} x_i\xi_i] \leftarrow e / N$.

In the above step 3, the fuzzy simulation process of expected value of $E[f(\xi)]$ is as following step 1 to step 8.

Step 1 Set $g = 0$.

Step 2 Generate θ_k evenly in Θ and make $Pos\{\theta_k\} \ge \varepsilon$, let $v_k = Pos\{\theta_k\}$, $k = 1,2,\ldots,N$, ε is a small number enough.

Step 3 Let $a = f(\xi(\theta_1)) \wedge \cdots \wedge f(\xi(\theta_N))$, $b = f(\xi(\theta_1)) \vee \cdots \vee f(\xi(\theta_N))$.

Step 4 Generate r evenly in $[a,b]$.

Step 5 If $r \ge 0$, then $g \leftarrow g + Cr\{f(\xi) \ge r\}$.

Step 6 If $r < 0$, then $g \leftarrow g + Cr\{f(\xi) \le r\}$.

Step 7 Repeat the fourth to sixth steps for N times.

Step 8 $E[f(\xi)] = a \vee 0 + b \wedge 0 + g \cdot (b - a) / N$.

B Train NN

We use BPA back propagation algorithm to train NN to approximate the objective value of mean chance $Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$ and the expected return rates $E[\sum_{i=1}^{n} x_i\xi_i]$ [24]. First, generate trainning data set, one trainning data is expressed as $\{x_1, x_2, \cdots, x_n, U_1, U_2\}$, where $U_1 = Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$ and $U_2 = E[\sum_{i=1}^{n} x_i\xi_i]$, U_1, U_2 can be computed by fuzzy random simulation. When generating input data $\{x_1, x_2, \cdots, x_n\}$, we set $x_i = x_i /(x_1 + x_2 + \cdots + x_n)$, $i = 1,2,\ldots,n$, Which ensure that $\sum_{i=1}^{n} x_i = 1$ always holds. Then use BPA back propagation algorithm to train NN. The training purpose is to find the most suitable weights ω that can minimize the error between the output of NN and U_1, U_2. It is usually enough to train the NN with one hidden layer. In the paper, the NN has one hidden layer connecting the input layer and the output layer in a feed-forward way and has two neurons in the output layer.

Supposing the NN has l neurons in the input layer, p neurons in the hidden layer and m neurons in the output layer. Now, there are N samples

$$\{x_{k,1}, x_{k,2}, \cdots, x_{k,l}; d_{k,1}, d_{k,2}, \cdots, d_{k,m}\},$$

$k = 1,2,\cdots,N$.

When the *k*-th sample is used, the outputs of the hidden neurons are

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$$x_{k,i}^1 = \sigma(\sum_{j=1}^{l} \omega_{ij}^0 x_{k,j} + \omega_{i0}^0),\ i = 1,2,\cdots,p\ .$$

And the outputs of the NN are

$$y_{k,i} = \sum_{j=1}^{p} \omega_{ij}^1 x_{k,j}^1 + \omega_{i0}^1,\ i = 1,2,\cdots,m$$

C Genetic algorithm:

Initialization process: We randomly initialize pos_size number of chromosomes, a chromosome is expressed as $(x_1, x_2, \cdots, x_n)$, $x_1, x_2, \cdots, x_n$ are randomly generated in the interval [0,1]. Let $x_i = x_i /(x_1 + x_2 + \cdots + x_n)$, $i = 1,2,\ldots,n$, which ensure that $\sum_{i=1}^{n} x_i = 1$ always holds. Then check their feasibility by NN, if $E[\sum_{i=1}^{n} x_i \xi_i] \geq \mu$, it is a feasible chromosome .

Selection process:We select chromosomes by spinning the roulette wheel such that the better chromosomes will have. The selection process is as follows:[24]

Firstly, If there are pos_size chromosomes $V_1, V_2, \cdots, V_{pop\_size}$ at the current generation, we can order these chromosomes from good to bad, the better the chromosomes is, the smaller the ordinal number it has. Let a parameter $a \in (0,1)$ in the genetic system be given, we can define the rank-based evaluation function as follows

$$eval(V_i) = a(1-a)^{i-1},\ i = 1,2,\ldots, pop\_size$$

Note that $i = 1$ means the best chromosome, $i = pop\_size$ means the worst one.

Secondly, calculate the cumulative probability q_i for each chromosome V_i,

$$q_0 = 0 \quad , \quad q_i = \sum_{j=1}^{i} Eval(V_j) \quad ,$$

$i = 1,2,\ldots, pop\_size$.

where $Eval(V)$ is evaluation function.

Thirdly, generate a random number r in $(0, q_{pop\_size}]$, and select the chromosome V_i if r satisfies $q_{i-1} < r < q_i$.

Fourthly, repeat the third step *pop_size* times and obtain *pop_size* copies of chromosome.

Crossover operation: A crossover parameter p_c is defined first[24]. Repeating the following process from $i = 1$ to pos_size : generating a random number r from the interval [0, 1], the chromosome V_i is selected as a parent if $r < p_c$. We denote the selected parents by $V_1', V_2', V_3', \ldots$,and divided them into the following pairs: (V_1', V_2'), (V_3', V_4') , $(V_5', V_6'), \ldots$. The crossover operation on each pair is illustrated by (V_1', V_2'), At first, we generate a random number c from the open interval (0,1), then the operator on V_1' and V_2' will product two chile X and Y as follows:

$$X = cV_1' + (1-c)V_2',\quad Y = (1-c)V_1' + cV_2'$$

If $X = (x_1, x_2, \cdots, x_n)$, $Y = (y_1, y_2, \cdots, y_n)$, Let $x_i = x_i /(x_1 + x_2 + \cdots + x_n)$, $y_i = y_i /(y_1, y_2, \cdots, y_n)$, $i = 1,2,\ldots,n$, which ensure that $\sum_{i=1}^{n} x_i = 1$ and $\sum_{i=1}^{n} y_i = 1$ always hold.

Checking whether $E[\sum_{i=1}^{n} x_i \xi_i] \geq \mu$ and $E[\sum_{i=1}^{n} y_i \xi_i] \geq \mu$ through NN, if both children are feasible, then we replace the parents with them. If not, we keep the feasible one if it exists, and then redo the crossover operator by regenerating a random number c until two feasible children are obtained or a given number of cycles is finished.

Mutation operation[24]: We define a parameter p_m as the probability of mutation. This probability gives us the expected number of $p_m \cdot pos\_size$ of chromosomes undergoing the mutation operations. Repeating the following steps from $i = 1$ to pos_size : generating a random number r from the interval [0,1], the chromosome V_i is selected as a parent for mutation if $r < p_m$. For each selected parents V_i, we mutate it in the following way. Let M be an appropriate large positive number. We choose a mutation direction d in R^n randomly. Let $X = V + M \cdot d$, If $X = (x_1, x_2, \cdots, x_n)$, Let $x_i = x_i /(x_1 + x_2 + \cdots + x_n)$, checking the feasibility through NN, If X is not feasible, we set M as a random number between 0 and M until it is feasible. If the above process cannot find a feasible solution in a predetermined number of iterations, then we set $M = 0$.

D Hybrid intelligent algorithm

The hybrid intelligent algorithm that is integrated fuzzy random simulation, genetic algorithm and NN is summarized as follows[24]:

Step 1 Generate training data set for the following uncertain functions by fuzzy random simulation.

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$$U_1 : x \to Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$$

$$U_2 : x \to E[\sum_{i=1}^{n} x_i\xi_i]$$

Step 2 Train NN to approximate the objective value of mean chance $Ch^a(\sum_{i=1}^{n} x_i\xi_i \le R_0)$ and the expected return rates $E[\sum_{i=1}^{n} x_i\xi_i]$

Step 3 Determine the population size pos_size, crossover probability p_c, mutation p_m in genetic algorithm.

Step 4 Initialize feasible pos_size chromosomes. Use the trained NN to check the feasibility of chromosomes.

Step 5 Update the chromosomes by crossover and mutation operations in which the feasibility of offspring may be checked by the trained neural network.

Step 6 Calculate the objective values for all chromosomes by the trained neural network.

Step 7 Compute the fitness of each chromosome according to the objective values.

Step 8 Select the chromosomes by spinning the roulette wheel.

Step 9 Repeat the fifth to eighth steps for a given number of cycles.

Step 10 Report the best chromosome as the optimal solution.

The method to solve model(2) is similar.

V NUMBER EXAMPLE

To illustrate the optimization idea and to test the effectiveness of the proposed algorithm, two numerical example is presented here. Supposing there are five kinds of loan in model(1) and model (2), each return rate is fuzzy random variable, described as follows.

$\xi_1 = (\rho_1 - 0.012, \rho_1 + 0.045, \rho_1 + 0.075, \rho_1 + 0.075)$, $\rho_1 \sim N(0.01, 0.01^2)$;

$\xi_2 = (\rho_2 - 0.015, \rho_2 + 0.06, \rho_2 + 0.06)$, $\rho_2 \sim N(0.02, 0.03^2)$;

$\xi_3 = (\rho_3 - 0.02, \rho_3 + 0.04, \rho_3 + 0.085, \rho_3 + 0.085)$, $\rho_3 \sim N(0.01, 0.02^2)$;

$\xi_4 = (\rho_4 - 0.02, \rho_4 + 0.05, \rho_4 + 0.09, \rho_4 + 0.09)$, $\rho_4 \sim N(0.03, 0.03^2)$;

$\xi_5 = (\rho_5 - 0.016, \rho_5 + 0.08, \rho_5 + 0.08)$, $\rho_5 \sim N(0.02, 0.04^2)$

Let $R_0 = -0.02$, $\mu = 0.05$, the model(1) is formulated as follows:

$$\begin{cases} \min Ch^a(\sum_{i=1}^{n} x_i\xi_i \le -0.02) \\ s.t. \\ \quad E[\sum_{i=1}^{n} x_i\xi_i] \ge 0.05 \\ \quad \sum_{i=1}^{n} x_i = 1 \\ \quad x_i \ge 0,\ i = 1,2,\cdots,n \end{cases} \tag{3}$$

the model(3) is solved through running hybrid intelligent algorithm, the parameters in the algorithm are set as follows: 500 cycles in simulation, 2000 data in NN(NN has 5 input neurons, 15 hidden neurons, 2 output neuron), 400 generations in GA, the population size $pop\_size = 30$, the crossover probability $P_c = 0.3$, the mutation probability $P_m = 0.2$. The run of the hybrid intelligent algorithm shows the best allocation proportion is $X^* = (0.4348, 0.0994, 0.2103, 0.2124, 0.0431)$, the minimal mean chance of the return rates less than the preset bad outcome -0.02 is 0.073272. The genetic process of algorithm is shown as Fig.2:

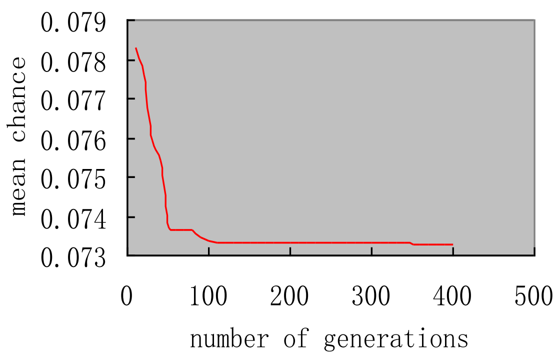

Fig.2 Genetic process of algorithm for model(3)

In order to further test the effectiveness of the designed algorithm, we use more numerical experiments with different values of parameters in the GA. The results are shown in Table 1.

Table 1 Comparison of objective value for model(3) at different parameters in the GA

Number of generations	pos_size	P_c	p_m	Objective value
400	30	0.3	0.2	0.073272
400	50	0.5	0.2	0.073232
400	80	0.3	0.5	0.073221
500	60	0.1	0.4	0.073222
500	100	0.6	0.3	0.073225
800	30	0.3	0.3	0.073226
800	90	0.3	0.2	0.073228
1000	70	0.2	0.3	0.073222
1000	30	0.3	0.2	0.073261

From table 1, we can see when different values of parameter in GA are set, the objective value changes very tiny, so the designed algorithm is robust to set parameters and effective to solve the model(3).

Let $R_1 = 0.07$, $\mu = 0.05$, the model(2) is formulated as follows:

$$\begin{cases} \max Ch^a(\sum_{i=1}^{n} x_i\xi_i \geq 0.07) \\ s.t. \\ \quad E[\sum_{i=1}^{n} x_i\xi_i] \geq 0.05 \\ \quad \sum_{i=1}^{n} x_i = 1 \\ \quad x_i \geq 0, \; i = 1,2,\cdots,n \end{cases} \qquad (4)$$

Through running hybrid intelligent algorithm we solve model(4), the parameters setting are as same as above. The run of the hybrid intelligent algorithm shows the maximal mean chance of the return rates more than the prospective return rate 0.07 is 0.556277, the best allocation proportion is $X^* = (0.0192, 0.0059, 0.0363, 0.9251, 0.0136)$, the genetic process of algorithm is shown as Fig.3:

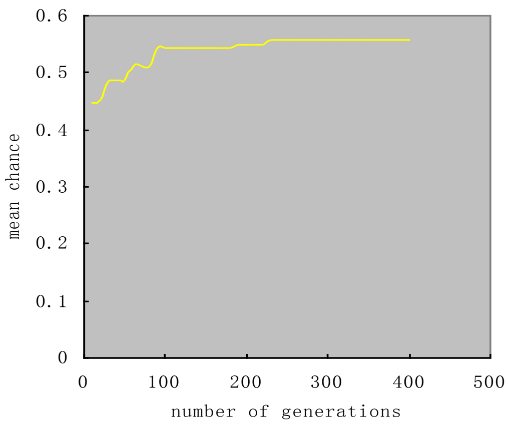

Fig.3 Genetic process of algorithm for model(4)

Similarly, we test the effectiveness of the designed algorithm for model(4) through setting different values of parameters in the GA. The results are shown in Table 2.

From table 2, we can see that the designed algorithm is robust to set parameters and effective to solve the model(4).

Table 2 Comparison of objective value for model(4) at different parameters in the GA

Number of generations	pos_size	P_c	p_m	Objective value
400	30	0.3	0.2	0.556277
400	50	0.5	0.2	0.567125
400	80	0.3	0.5	0.573905
500	60	0.1	0.4	0.574286
500	100	0.6	0.3	0.548707
800	30	0.3	0.3	0.557875
800	90	0.3	0.2	0.579590
1000	70	0.2	0.3	0.570203
1000	30	0.3	0.2	0.568431

Ⅵ CONCLUSION

In the paper, we discuss the optimization of loan portfolio under fuzzy random environment, give two new dependent-chance programming models of loan portfolio based on mean chance and design hybrid intelligent algorithms integrating genetic algorithm, fuzzy random simulation and neural network to solve the models. At the end, two numerical examples are presented to illustrate the modelling idea and the effectiveness of the proposed algorithm.

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