Risk Assets Optimized Configuration Under Integrated Risks-in View of Banker'S Risk Appetite

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***Abstract* — As pointed out by "Basel New Capital Accord", modern commercial banks should pay attention to the relevance of market risk, credit risk and operational risk when managing them. This thesis starts with the risk appetites of different bankers, proposes the risky assets optimized configuration of commercial banks basic on risk integration measurement model, and provides the solution algorithm combining stochastic simulation, neural network and genetic algorithms. With the optimized configuration of market risk assets and credit risk assets of Bank of China (BOC) and China Merchants Bank (CMB) as example, this thesis has validated the effectiveness of model and solution. This model indicates that basic on historical data, bankers can determine the level of integrating risk according to their risk appetites. This thesis is the forward-looking for the optimized configuration of risk assets of commercial banks, and provides new ideas for assets configuration.**

Keywords - insert integrating risk; risk asset configuration; risk appetite; monte carlo simulation

I. INTRODUCTION

With constant development and increasing complexity of financial market, risk management is greatly challenged. The high incidence of global financial crisis makes the correlation and co-movement of risks become the focus. "Basel New Capital Accord" further defines the thought of comprehensive risk management and points out the three great risks faced by commercial banks, market risk, credit risk and operational risk. In risk management, the banks should also consider the relevance between these 3 risks. Risk assets configuration is the most critical step for risk and commercial banks must give enough attention and seize on pre-control on risks. Risky assets refer to the part of assets with high risks caused by the uncertainty of future yield in the asset structure of commercial banks and non-bank financial institutions. According to the risks carried by assets, assets can be classified into market risk assets, credit risk assets and operational risk assets. For example, trading assets are often exposed to market risks, including trading financial assets, salable financial assets, long-term equity investments, derivative financial assets, held-to-maturity investments and so on; assets exposed to credit risks include the loan and advance issued by enterprise. Risk appetite refers to the total risk exposure a bank is willing to undertake or reserve basic on the return equilibrium point of some risk. It reflects the business strategy and risk strategy of bank, and the expectation of stakeholders. Risk appetite is set through the discussion of management level or approved by the board. The risk appetite of bankers is usually embodied in the configuration of integral risk assets and relevant risk assets.

On the one hand, when Copula function is applied to the management of risks in banking industry, it mainly serves the integration of multiple risks. As this type of integrating risk measurement is basic on existing risk asset configuration, it can only provide an objective reflection about current risk level of commercial banks and cannot offer guidance for further risk assets configuration of commercial banks. On the other hand, though related regulations raise a series of fundamental requirements for risk management of bankers, they still have space to configure corresponding risk assets according to their risk appetite. This thesis will start with the risk assets configuration strategy of commercial banks and then discuss about how bankers make efficient risk assets configuration after determining integrating risks according to their own risk appetite to obtain the maximum yield on the premise of satisfying the requirements for risk level and earnings distribution.

II. LITERATURE REVIEW

In recent years, scholars have started with studying the possibility to build a model for the integrated measurement of multiple risks faced by commercial banks. During this process, the model basic on Copula function becomes the focus of research. In view of the defect of traditional VaR measurement method, Ning Hongquan (2012) considered the nonlinear correlation of financial markets and the dynamic changes of tail actions, and proposed the risk value measurement model basic on time varying Copular and Garch model[1]. Liu Xiangdong, et al (2013) chose credit risks and market risks as the influencing factors of integrating risks and evaluated the integrating risk level of 12 listed commercial banks in China, and employed kernel density estimation to fit marginal distribution[2]. Xi Yuan and Changquan Chen (2014) considered the dynamic correlativity of financial variables and proposed the

GARCH-Copula-CoVar method to measure the contribution of systematic risks and marginal risks of Chinese listed banks by referring to the methods of Adrian and Brunnermeier (2011) [3,4]. Guo Lifu, Gao Tiemei and Yao Jian (2013) constructed correlation coefficients near the tail basic on Copula function and POT model of extreme value theory, and then empirically analyzed its effectiveness in financial contagion[5]. Du Ziping and Gao Libao (2013) studied the contagion approaches of subprime crisis and European debt crisis by Copula theory[6]. Valdés and Roldán (2013) employed Copula method in studying the dependency of Mexican and Brazilian financial markets, which works better than common correlation analysis in obtaining subjective and true results. They also made analysis by Gaussian copula, Gumbel copula and Clayton copula, and found that the dependency structure in financial markets of two countries was strengthened after the financial crisis in 2008[7]. Shams and Haghighi (2013) proposed the condition dependency model integrating Copula method and GARCH, and studied the risk value of stocks with VaR method[8].

As for concrete commercial bank risk measurement, Zhou Qiao and Zhang Shuguang (2012) proposed a feasible evaluation method for the loss caused by operation risk in Basel Agreement. They classified the operational risk events collected by Bayesian network and established data network, and respectively evaluated the occurrence frequency of various loss events and distribution parameters of losses. Copula function was employed to treat related nodes and evaluate population distribution VaR and ES[9]. Lu Jing and Zhang Jia (2013) considered the features of fat-tailed operational risks according to the requirements of Basel Agreement and employed POT extreme value model to evaluate the marginal distribution of multiple operational risk units, and then depicted the relevance between operational risk units with multi-element Copula function, and then calculated the value at risk. They further pointed out that the application of Copula function to calculate the relevance of operational risks can not only improve the accuracy of evaluation, but also can provide risk decentralization effect of assets portfolio, lower down capital requirement of operational risks, and create foundation to improve the profit-making capacity of commercial banks[10]. Ming Ruixing and Xie Quan (2013) analyzed the relevance structure of various operational risks of Chinese commercial banks with tail-related Copula function, applied POT model of extreme value theory to effectively capture the fat tail of loss, and built tail-related Copula model to calculate overall VaR value of operational risks[11]. Xie Chi, Zhou Liangqiu and Yue Hanqi, et al (2012) built a time-varying multivariate model and applied Monte Carlo simulation technology to calculate VaR. This way can exactly measure the risks of RMB exchanging for USD, Euro, Yen and HKD on commercial banks[12]. When discussing on loan portfolio optimization, Liu Yanping and Fu Ying (2012) applied Copula function fitting loan yield joint distribution function in order to avoid the high risk of default and loan caused by extreme events. They employed K-S inspection to choose optimal Copula function to measure the default relevance between loans, and established loan portfolio optimization model basic on risk control of Copula function. This model can solve some problems caused by insufficient default data and the hypothesis that yield rate complies with normal distribution[13]. In measuring portfolio credit risks, Tang Zhenpeng and Huang Youpo (2013) has discovered that the VaR and ES estimate value of Copula method under various common multi-variant Copula dependency structures is closer to practical risk. Therefore, Vine Copula is applied to describe default dependency structure and measure portfolio credit risk basic on this[14]. Bologov (2013) proposed the credit risk model of portfolio assets basic on Copula method and with a basket of credit assets as object[15].

Most of current studies start with the measurement of risks in current assets configurations. Though Copula function can provide more objective and precise risk value by integrating various kinds of risks, its guidance on commercial banks in risk assets configuration from strategy and controlling integral risks is limited. This thesis will start with the optimization of risk assets configuration and discuss about the strategy and planning of risk assets configuration of commercial banks under the premise of controlling integral risks.

III. MODEL, VARIABLES AND DATA

A. *Copula-VAR model for integrating risk measurement*

1) *Copula function definition*

Usually the consumption area of electrical power is very wide, the chances of any kind of unforeseen accident, fault or abnormal condition is very common. Somewhere in a power utility network, an unforeseen accident creates a short circuit. The long transmission lines are bare and nakedly exposed to atmosphere. A joint distribution can be a Copula function whose form describes the relevance structure of variables. As Copula function is the function connecting joint distribution and marginal distribution, it is also called as connecting function. We will provide a brief introduction to the definition and nature of Copula function in the following.

Nelsen (1999) points out that n-variable copula function refers to the function containing the following natures[16,17]:

(1) $C = I^N = [0,1]^N$;

(2) C is monotone increasing for each variable.

(3) The marginal distribution of C meets $C_n(u_n) = C(1,\ldots,1,u_n,1,\cdots 1) = u_n$, where, $u_n \in [0,1]$,

According to the type of distribution function, copula function can be classified into ellipse Copula function, including Copula, t-copula and Archimedes Copula function, including Gumbel copula function, Clayton copula function, Frank copula function and so on. Table 1 provides a summary of distribution characteristics of various Copula functions.

TABLE I CHARACTERISTICS OF DIFFERENT COPULA FUNCTIONS

Copula function	**Elliptical Copula function family**		**Archimedean Copula function family**		
	Normal-Copula	t-Copula	Clayton-Copula	Gumbel-Copula	Frank-Copula
Characteristics of distribution functions	Symmetric distribution without tail features	Symmetric distribution with tail features	Asymmetrical distribution with thicker lower tail	Asymmetrical distribution with thicker upper tail	Symmetric distribution with thicker upper and lower tail

2) Application of copula function in integrating risks

Previously, the risk management of commercial banks starts with a single risk, determines its yield rate distribution, and then provides the VaR under given confidence level. In measuring integrating risks, after determining the marginal distribution of various risks and the form of Copula connecting function, we can connect marginal distribution of risks through Copula function and construct distribution function of integral risks of commercial banks. Assuming that random variable x_m, x_c and x_o respectively represents the yield rate of market risk, credit risk and operational risk encountered by commercial banks, the corresponding $F_m\left(x_m\right)$, $F_c\left(x_c\right)$ and $F_o\left(x_o\right)$ is respectively the marginal distribution of market risk, credit risk and operational risk. The joint distribution function composed by these 3 marginal distributions is Copula function:

$$F(x_m, x_c, x_o) = C\left(F_m\left(x_m\right), F_c\left(x_c\right), F_o\left(x_o\right)\right) \quad (1)$$

The VaR of risk portfolio can be obtained by the following formula:

$$P(\omega_m x_m + \omega_c x_c + \omega_o x_o \rangle \delta) = \int\limits_{\omega_m x_m + \omega_c x_c + \omega_o x_o \rangle \delta} dC\left(F_m\left(x_m\right), F_c\left(x_c\right), F_o\left(x_o\right)\right) \quad (2)$$

Where, ω_m, ω_c, and ω_o respectively represents the proportion of market risk, credit risk and operational risk in investment portfolio, and $\omega_m + \omega_c + \omega_o = 1$ is true. δ is a designated value relative to significance level α. If $F_m\left(\cdot\right)$, $F_c\left(\cdot\right)$ and $F_o\left(\cdot\right)$ is continuous, it can be known from Sklar principle that connection function C is unique. As for 3D Copula function, we can define corresponding density function:

$$f_{x_m, x_c, x_o}(x_m, x_c, x_o) = f_{x_m}(x_m) f_{x_c}(x_c) f_{x_o}(x_o) c\left(F_m\left(x_m\right), F_c\left(x_c\right), F_o\left(x_o\right)\right) \quad (3)$$

As long as the marginal distribution function of market risk, credit risk and operational risk and connecting function to describe the relevance between risks is determined, we can obtain the distribution function of integrating risk of commercial banks, and then calculate the risk value of integrating risk according to VaR method.

B. Assets configuration optimization model under the control of integrating risks

This thesis determines the distribution of earnings according to historical earning data and then obtains the probability function of earnings, which has certain uncertainty. Therefore, the risk appetite of bankers in integral risk and business portfolio can be determined by setting the probability of risks in related assets configuration. Among them, as for overall risk, it can be determined by controlling the probability of the potential loss of bank lower than risk value; business portfolio appetite can be determined by controlling the probability of proportion of one business earning in total earnings exceeding appointed proportion. On this basis, we can establish uncertainty planning model with the goal to maximize total earnings of various risk assets.

Assuming that ξ_1, ξ_2, ξ_3 are random variables representing the yield rate for market risk assets, credit risk assets and operational risk assets, V is the preset risk value of integrating risk control. Then, we can establish the following asset configuration optimization model under integrating risk control.

$$\max \quad w_1\xi_m + w_2\xi_c + w_3\xi_o \quad (4)$$

s.t.

$$\Pr\left\{w_1\xi_m + w_2\xi_c + w_3\xi_o \ge -V\right\} \ge 1-\alpha \quad (5)$$

$$\Pr\left\{\frac{w_2\xi_c}{w_1\xi_m + w_2\xi_c + w_3\xi_o} \ge \beta\right\} \ge \gamma \quad (6)$$

$$0 \le F_m\left(\xi_m\right) \le 1 \quad (7)$$

$$0 \le F_c\left(\xi_c\right) \le 1 \quad (8)$$

$$0 \le F_o\left(\xi_o\right) \le 1 \quad (9)$$

$$0 \le C_c\left(F_c\left(\xi_c\right) \mid F_m\left(\xi_m\right)\right) = \frac{\partial C_{m,c,o}\left(F_m\left(\xi_m\right), F_c\left(\xi_c\right), 1\right)}{\partial F_m\left(\xi_m\right)} \le 1 \quad (10)$$

$$0 \le C_c\left(F_o\left(\xi_o\right) \mid F_m\left(\xi_m\right), F_c\left(\xi_c\right)\right) = \frac{\dfrac{\partial^2 C_{m,c,o}\left(F_m\left(\xi_m\right), F_c\left(\xi_c\right), F_o\left(\xi_o\right)\right)}{\partial F_m\left(\xi_m\right)\partial F_c\left(\xi_c\right)}}{\dfrac{\partial^2 C_{m,c,o}\left(F_m\left(\xi_m\right), F_c\left(\xi_c\right), 1\right)}{\partial F_m\left(\xi_m\right)\partial F_c\left(\xi_c\right)}} \le 1 \quad (11)$$

$$\alpha, \beta, \gamma \in [0,1] \tag{12}$$

Formula (4) is target function indicating the goal of model is to maximize the earnings of various risk assets; Formula (5) and (6) depicts the risk appetite of bankers. Formula (5) is the constraint conditions of confidence level indicating that under the uncertainties of yield rates of various risk assets, the potential loss of bank should be within $1-\alpha$ and must not exceed risk value V ; Formula (6) indicates under the uncertainties of yield rates of various risk assets, the bank restrains the proportion of credit business earning in total earnings to guarantee the credit and loan is the main business, namely, the proportion of credit business earning in total earnings should exceed β under the possibility of γ . Formula (7) ~ (9) is the value constraint of marginal distribution function of market earning, credit earning and operational earning. Formula (10) ~ (11) is the value constraint the marginal distribution of integrating risk copula function.

The model contains probability constraint conditions and is a random chance constraint planning model in uncertain planning. As random chance constraint planning model is very complicated and it is very difficult to obtain analytical solution in risk integration with copula connecting function, it cannot directly obtain the optimal solution of model. Usually, the solution is obtained by combining stochastic simulation and intelligent optimization algorithm. This paper involves the following solution process with combined intelligent algorithm.

Step 1: according to the yield rate of risk assets of commercial banks, determine the marginal distribution function of market risk, credit risk and operational risk.

Step 2: choose copula function to connect marginal distribution, estimate and verify fitting parameters. Then, we can obtain the joint distribution of (ξ_m, ξ_c, ξ_o).

Step 3: create input and output data for the following uncertainty functions with stochastic simulation technology.

$$\mathrm{U}_1:(w_m, w_c, w_o) \to \Pr\left\{\frac{w_c\xi_c}{w_m\xi_m + w_c\xi_c + w_o\xi_o} - \beta \ge 0\right\} \tag{13}$$

$$\mathrm{U}_2:(w_m, w_c, w_o) \to \max\{V|\Pr\{w_m\xi_m + w_c\xi_c + w_o\xi_o \ge -V\} \ge 1\text{-}\alpha\} \tag{14}$$

The simulated data input process of uncertainty function is as follow: randomly create the weight of market risk assets, w_m with average distribution [0, 1]; credit risk assets weight, w_c with average distribution$[0, 1-w_m]$; operational risk assets weight, w_c with average distribution $[0, 1-w_m-w_c]$. Up to now, we can create a group of risk asset configuration plan(w_m, w_c, w_o).

Simulated output data process of uncertainty function is as follow: ① set $N'=0$; ② create a group of earning data (ξ_m, ξ_c, ξ_o) which can meet Copula joint distribution function. Concrete method is to create random number u according to average distribution [0, 1], namely $\xi_m = F_m^{-1}(u)$, and then create random number v by average distribution [0, 1]; set $C_c(F_c(\xi_c) | F_m(\xi_m)) = v$, and obtain inverse solution $F_c(\xi_c)$ by constraint condition (10), and confirm $\xi_c = F_c^{-1}(v)$, and at last, create random number w by average distribution [0, 1]. Set $C_c(F_o(\xi_o) | F_m(\xi_m), F_c(\xi_c)) = w$ and obtain inverse solution $F_o(\xi_o)$ by constraint condition (11), and confirm $\xi_o = F_o^{-1}(w)$. Up to now, we can produce a group of earning data (ξ_m, ξ_c, ξ_o) which can meet copula joint distribution function; ③ bring (ξ_m, ξ_c, ξ_o) into formula $\frac{w_c\xi_c}{w_m\xi_m + w_c\xi_c + w_o\xi_o}$, and figure out the result. If it meets $\frac{w_c\xi_c}{w_m\xi_m + w_c\xi_c + w_o\xi_o} - \beta \ge 0$, then $N'++$; ④ repeat step② and ③ for sufficient times N ; ⑤ calculate $p = N'/N$, namely, the output data of uncertainty function U_1 relative to current risk asset configuration plan(w_m, w_c, w_o). Likewise, we can obtain the output data of uncertainty function U_2 relative to current risk asset configuration plan(w_m, w_c, w_o).

Step 4: when sufficient input and output data is produced. According to the data, train a neural network to get close to uncertainty function (13) and (14).

Step 5: initialize G risk assets configuration plans (w_m, w_c, w_o) as chromosomes, verify the feasibility of chromosome with the trained neural network in step 6, and retain feasible chromosomes to form the initial population.

Step 6: subject chromosomes to cross and mutation operation to create 2 new chromosomes. Verify the feasibility of chromosomes with trained neural network. Cross operation method is to add together the weights of various risk assets of two selected chromosomes, and then the result is divided by 2, namely $(w_{m\_new}, w_{c\_new}, w_{o\_new}) = \left(\frac{w_{m\_1} + w_{m\_2}}{2}, \frac{w_{c1} + w_{c2}}{2}, \frac{w_{o1} + w_{o2}}{2}\right)$. Mutation operation is implemented by certain probability. Concrete operation is to randomly exchange the three risk asset configuration plans in a chromosome.

Step 7: calculate the target function values of all chromosomes with neural network and treat the values as the fitness of chromosome.

Step 8: choose chromosomes with roulette strategy as the parent of next evolution.

Step 9: repeat step 6~8 until reaching to given loop optimization times and output the best chromosome as optimal solution as well as target function value which is the yield rate of risk assets under optimal risk asset configuration.

C. Sample selection

This thesis selects BOC and CMB as research objects and focuses on the strategy of two commercial banks in the configuration of market risk assets and credit risk assets. The market risks of commercial banks are usually from the financial assets which can be affected by market price, so we can divide the total earnings of this part of assets by its total amount to calculate the yield rate of market risk assets. As the risks in financial market are macro risks, each subject is largely related with market risks. Therefore, related studies measure the risks by the correlation indexes of stock market. The Shanghai and Shenzhen 300 index considered by this paper covers about 60% of stocks in Shanghai and Shenzhen market, and has certain representativeness. This thesis chooses the yield rate of Shanghai and Shenzhen 300 index as proxy variable to measure yield rate of risk assets of commercial banks. As for credit yield rate, as most credit businesses of commercial banks are loan and the corresponding earnings are interest income, this thesis treats the interest income in the profit statement of commercial banks as the earnings of credit risk assets and the loans and advances in balance sheet as the total amount of credit assets. Divide one by the other to obtain credit asset yield rate. Market yield rate and credit yield rate is presented by logarithm yield rate. As the accounting system of Chinese commercial banks is changing, to maintain the consistency of sample data indexes, the data cycle of samples is from the 1st quarter of 2007 to the 3rd quarter of 2013.

IV. EMPIRICAL RESULT AND ANALYSIS

A. Marginal distribution and correlation test

Firstly, the paper makes descriptive statistics and normality test on the sample values of yield rates of Shanghai and Shenzhen 300 (CSI 300), Bank of China (BOC) credit and China Merchants Bank (CMB) credit. The paper employs Kolmogorov-Smirnov (K-S) inspection method suitable for small samples. The result of inspection is shown in table II.

TABLE II DESCRIPTIVE STATISTICS AND NORMALITY TEST

Yield Rate	**Mean Value**	**Variance**	**Skewness**	**Kurtosis**	**K-S normality test**	
					Z statistics	**P value**
CSI 300 return	0.0281	0.2414	0.4063	1.8161	0.7587	0.6189
BOC credit risk return	0.0189	0.0039	0.0579	1.7318	0.5220	0.8143
CMB credit risk return	0.0195	0.0033	1.5798	1.6030	0.5461	0.8241

There are 27 sample data of related variables. The critical value of statistics of K-S inspection is within n=20 and n=30. Under the significance level of 5%, the significant interval of statistics is 0.242～0.294. Therefore, when statistical value is larger than 0.242, we can regard that it accepts and complies with the original hypothesis of normal distribution. It can be seen from the result of K-S inspection from table 2 that the yield rate of Shanghai and Shenzhen 300 and credit earnings of 2 commercial banks can be considered to comply with normal distribution. After determining the marginal distribution of market yield rate and credit yield rate, connecting function is required to describe the related structure of market risks and credit risks. This paper chooses Gauss copula function of ellipse family, Gumbel copula function of Archimedes family, Clayton copula function, and Frank copula function as connecting function, and employs non-parametric estimation method to evaluate the related parameters of connection functions. Evaluation result is shown in table III.

TABLE III NON-PARAMETRIC EVALUATION RESULT OF CONNECTING FUNCTION

Banks	**Gauss Copula (ρ)**	**Gumbel copula (θ)**	**Clayton copula (θ)**	**Frank copula (θ)**
BOC	0.4589	1.3950	1.2168	3.0387
CMB	0.3581	1.4181	0.7006	2.9848

Considering the range of parameters in various connecting functions, the parameters of different connecting functions in table 3 are all within defined range. To choose optimal copula function, we need to verify the goodness of fit. This paper also employs K-S inspection method to calculate the max distance between Pula function and empirical distribution function and the P value. The result of inspection is shown in table IV.

TABLE IV P VALUE OF GOODNESS OF FIT FOR FITTING FUNCTION

Banks	**Gauss copula (θ)**	**Gumbel copula (θ)**	**Clayton copula (θ)**	**Frank copula (θ)**
BOC	0.4589	1.3950	1.2168	3.0387
CMB	0.3581	1.4181	0.7006	2.9848

Larger P value indicates better imitative effect of connection function. It can be seen that Gumbel copula function is the most suitable for BOC, Frank copula function for Bank of Communications and Gumbel copula function of CMB.

B. Analysis on risk asset configuration results of commercial banks

The paper assumes that the target proportion of earnings of credit risk assets of two banks in total earnings is $\beta = 0.75$ and the probability value of earnings of credit risk assets meeting the requirement is $\gamma = 0.95$. Assuming that BOC and CMB plans to control the overall risk value of two risk assets at 0.2179 and 0.1903, and VaR confidence level is $1-\alpha=0.95$, then we can conclude how two commercial banks should configure risk assets under these requirements to achieve the maximum yield rate. In concrete calculation, Matlab2014a is employed for programming solution. Set the scale of population is 30 and mutation probability is 0.3. Stochastic simulation technology is employed to produce input and output data for uncertainty function and train a neural network to get close to uncertainty function, which contains 2 input nerve cells, 8 nerve cells in hidden layer and 2 output nerve cells. At last, we solve by intelligent algorithm, including 6000 stochastic simulation times (the number of cycles to obtain the value of single uncertainty function), 2000 training samples, 2000 times of inheritance iterations. The final result is shown in table V.

TABLE V OPTIMAL CONFIGURATION RESULT OF MARKET RISK ASSETS AND CREDIT RISK ASSETS

Banks	Weight of market risk assets	Weight of credit risk assets	Comprehensive yield rate
BOC	0.3146	0.6854	0.021757
CMB	0.2981	0.7019	0.021602

It can be seen from the result of risk assets configuration that under general control on market risks and credit risks, commercial banks can make optimized configuration of related risk assets and improve capital utilization efficiency to obtain optimal comprehensive yield rate. Among the two banks, as BOC has a larger preset risk value, it requires more earnings to compensate and obtain more comprehensive yield. On the other hand, the historical yield rate of BOC is the highest and there are more businesses, so the weight of market risk assets is larger.

V. CONCLUSION

Basic on the copula-VaR risk integrating measurement model, this paper discusses on the risk asset configuration of commercial banks under the risk appetite of bankers. By related historical data, the paper has established the probability distribution function of yield rate and the uncertainty planning model which is with yield maximization of risk asset portfolio as target function and integrating risk control, risk asset distribution as constraint conditions. According to the uncertainty of yield rate, the paper confirms the uncertainty function of constraint conditions and employs asset portfolio simulation and neural network algorithm to get close to uncertainty function. On this basis, genetic algorithm is employed to solve. At last, the thesis validates the feasibility and effectiveness of this method by referring to the related data of BOC and CMB in the first quarter of 2007 and 3rd quarter of 2013. The risk asset configuration thought of this thesis can play as guiding role in risk asset configuration planning of commercial banks and provides a reference to commercial banks when making reasonable prospective earnings target and controlling related risks.

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