Journal of Computers Vol. 35 No. 4, August 2024, pp. 133-142
doi: 10.53106/199115992024083504010

Research on Dynamic Credit Evaluation of Family Farms and Ranches Based on Weight Assembly Optimization Model

Tongtong Wang and Zhanjiang Li*

College of Economics and Management, Inner Mongolia Agricultural University, Hohhot, China
{wangtongtong4009, lizhanjiang582}@163.com

Received 1 July 2023; Revised 11 July 2023; Accepted 11 July 2023

Abstract. Most of the existing credit evaluation index weight estimation models only consider the cross-sectional data of a single time point, and do not consider the characteristics of the index data change over time, and the obtained index weights cannot reflect the objective data change ability of multiple time points in the sample, so this paper proposes a new weight calculation model based on the dynamic assembly weight of particle swarm optimization (PSO) algorithm and empirical analysis on Family Farms and Ranches (FF&R) in Inner Mongolia. Firstly, the weight of a single point static credit evaluation index with default identification ability is measured by the Fisher discriminant method, and secondly, a nonlinear programming equation is constructed to dynamically assemble the weights of each single time point by minimizing the overall deviation of the dynamic assembly weight of each time point weight, and the assembly weight of credit evaluation indicators that can reflect the data change ability of each time point is measured. Finally, the comprehensive credit evaluation score of each sample is calculated by linear weighting. The innovation point of this paper is to construct a nonlinear programming equation with the smallest sum of squares of the deviation between the weights of each time point and the assembly weight, and find the dynamic assembly weights that accurately reflect the change ability of data at each time point, which makes up for the disadvantage of ignoring the continuity of time in the traditional credit evaluation weight measurement method and not obtaining the weight of evaluation indicators reflecting the change ability of multiple time points.

Keywords: assembly weight, PSO algorithm, fisher discriminates, credit evaluation, Family Farms and Ranches

1 Introduction

In the credit evaluation index system of FF&R, different evaluation indicators have different status and influence, and it is especially important to assign weights to evaluation indicators that match their importance. The weight of the evaluation index directly affects the overall contribution of the index, so determining the scientific weight of the index is the premise and basis for effective credit evaluation. At present, most of the data used to calculate the weights come from the original data of a single point in time during the evaluation process. With social progress, technological development and the complexity of the problems faced by FF&R, the static data of a single point in time can no longer accurately measure the importance of the evaluation indicators, nor can they accurately identify the credit characteristics of FF&R, which may even lead to misjudgment of the credit characteristics of FF&R. Therefore, this paper first uses Fisher's data to identify the credit characteristics of FF&R. Therefore, in this paper, we first measure the single point-in-time static credit evaluation index weights with default identification ability by Fisher's discriminant method, and then construct a nonlinear programming equation with the minimum squared deviation of each point-in-time index weight and the set weight to find the dynamic set weight that accurately reflects the change ability of each point-in-time data, which makes up for the traditional credit evaluation weight measurement method that ignores the continuity of time and cannot get the dynamic set weight that accurately reflects the change ability of each point-in-time data. It compensates for the drawback that the traditional credit evaluation weight measurement method cannot obtain the evaluation index weights reflecting the change ability of data at multiple points in time by ignoring the time continuity.

The current status of research by scholars at home and abroad on the measurement methods of credit evaluation index weights and credit evaluation scores of FF&R is as follows:

(1) Current status of research on the weight measurement method of static credit evaluation index system

* Corresponding Author

Guozheng Zhang et al. (2017) used hierarchical analysis to construct a FF&R value assessment index system, measured the weights of each index by constructing a discriminant matrix, and made reasonable suggestions for the healthy development of family farms [1]. Zejiang Pan et al. (2019) used hierarchical analysis to construct the weights of the decision index system and built a decision model for the cultivation of new agricultural business entities [2]. Jingfeng Yuan et al. (2019) used hierarchical analysis to measure the evaluation index weights of 21 OPIs and combined fuzzy mathematics as well as expert evaluation methods to quantitatively grade OPIs [3]. Yong Lan et al (2021) measured the guideline level weights of FF&R credit evaluation indexes using entropy TOPSIS model, and suggested the relevant departments to improve the endogenous growth capacity of family farms [4]. Jinghui Xu et al. (2023) selected 24 indicators to construct a comprehensive evaluation score system of digital countryside development and measured the comprehensive score of digital countryside development by using factor analysis [5].

(2) Current status of research on dynamic credit evaluation methods

Most scholars study the idea of dynamic credit evaluation as linearly weighting the evaluation scores of multiple different time points of the sample with the time weights to obtain the final sample dynamic evaluation scores, and different scholars carry out the calculation of dynamic credit evaluation scores from the following aspects. Yajun Guo et al. (2007) proposed to measure the dynamic evaluation score by linearly weighting the evaluation scores of multiple time points with the time weight vector using nonlinear programming method [6]. Baofeng Shi et al. (2015) measured the time weights by matrix distance modified TOPSIS method and linearly weighted the static science and technology evaluation scores of 14 provincial administrative regions from 2009 to 2011 for the empirical analysis of dynamic evaluation [7]. Faming Zhang et al. (2018) proposed a dynamic credit evaluation method of TOPSIS-GRA with risk-resilient credit reward and punishment features [8]. Yanyan Yang et al. (2018) use a quadratic weighted evaluation model to obtain dynamic credit evaluation by information aggregation of data from static evaluation time points of Shi industrial enterprises [9]. Jingchun Feng et al. (2019) obtained dynamic credit values based on historical data by aggregating credit values of static time points with the help of time weights using 22 enterprises as an example [10].

(3) Current status of research on particle swarm optimization algorithms

Libiao Zhang et al. (2004) solved a non-inferior optimal solution to a multi-objective optimization problem by adopting different selection methods for the global and individual extremes of the particle swarm optimization algorithm [11]. Feifan Feng et al. (2017) used PSO algorithm to optimize the initial weights and thresholds of the neural network and construct a PSO-neural network landslide sensitivity prediction model [12]. Fengqing Wu et al. (2018) selected 21 indicators to build regional collaborative innovation capacity evaluation indexes and used PSO algorithm to construct innovation capacity prediction model [13]. Xiaojun Ma et al. (2019) applied PSO algorithm to enterprise credit rating, and the empirical results showed that the inclusion of PSO can improve the credit rating accuracy [14]. Ruoqin Yan et al. (2020) proposed to combine PSO algorithm with machine learning models to design plasma sensors, and the use of PSO algorithm can increase the speed of solution optimization [15].

The main shortcomings of the existing studies are: First, in the static credit evaluation process of FF&R, the indicator assignment methods do not accurately reflect the evaluation indicators' ability to discriminate between defaulting and non-defaulting FF&Rs; Second, in the dynamic credit evaluation process of FF&R, most of the existing studies weight the static credit scores to obtain the dynamic composite scores without considering measuring the dynamic weights, so that the final credit evaluation index set weights can accurately reflect the ability of objective data changes at each time point.

To address the shortcomings of the existing research, this paper takes 100 FF&Rs in Inner Mongolia as the credit evaluation object, firstly, it constructs a nonlinear programming equation with default discriminative ability by Fisher's discriminative method to measure multiple single-point static credit evaluation index weights, secondly, it constructs a nonlinear programming equation with minimum squared deviation between index weights and aggregation weights at each point in time, and uses PSO algorithm, finally, the dynamic credit evaluation scores of family farms are measured based on the dynamic aggregation weights.

2 Principles of Credit Evaluation of FF&Rs

(1) Scientific problem one and solution ideas

Question 1: In the existing static credit evaluation process of FF&Rs, what indicator weighting method can accurately reflect the ability of evaluation indicators to identify defaulting FF&Rs and non-defaulting FF&Rs,

and the stronger the ability to identify defaulting FF&Rs, the greater the weight of evaluation indicators should be.

To solve problem 1: 1) By constructing a nonlinear programming equation with the largest gap between default and non-default samples and the smallest gap within the group, we solve the indicator weights that reflect the greater the gap between default and non-default samples. This makes up for the shortcomings of the existing research evaluation index weights in identifying defaulted samples and non-defaulted samples. 2) The evaluation index weights that can significantly distinguish between defaulted and non-defaulted samples are solved by Fisher's discriminant method to construct a static credit evaluation model of FF&R with the ability to significantly distinguish between defaulted and non-defaulted samples. The deficiency that the index weights of the existing research credit evaluation model cannot reflect the default discrimination ability of the sample is remedied.

Question 2: In the existing dynamic credit evaluation process of FF&Rs, what method of measuring indicator weights can be used to minimize the overall deviation of indicator weights at each time point from the final indicator set weights, even if the final credit evaluation indicator set weights can accurately reflect the ability of objective data changes at each time point.

The idea of solving problem 2: 1) by constructing a nonlinear programming equation with the minimum sum of squared deviations of indicator weights and aggregation weights at each time point, we find the aggregation weights that accurately reflect the ability of data change at each time point, improve the reliability and credibility of credit evaluation results, and make up for the drawback that the evaluation indicator weights reflecting the ability of data change at each time point cannot be obtained in the traditional dynamic credit evaluation method; 2) by continuously PSO algorithm with iterative random particles solves the nonlinear programming model and measures the credit evaluation scores of FF&Rs at new time points by the final set weights.

Fig. 1 shows the dynamic credit evaluation model and application technology roadmap from the perspective of weight set optimization.

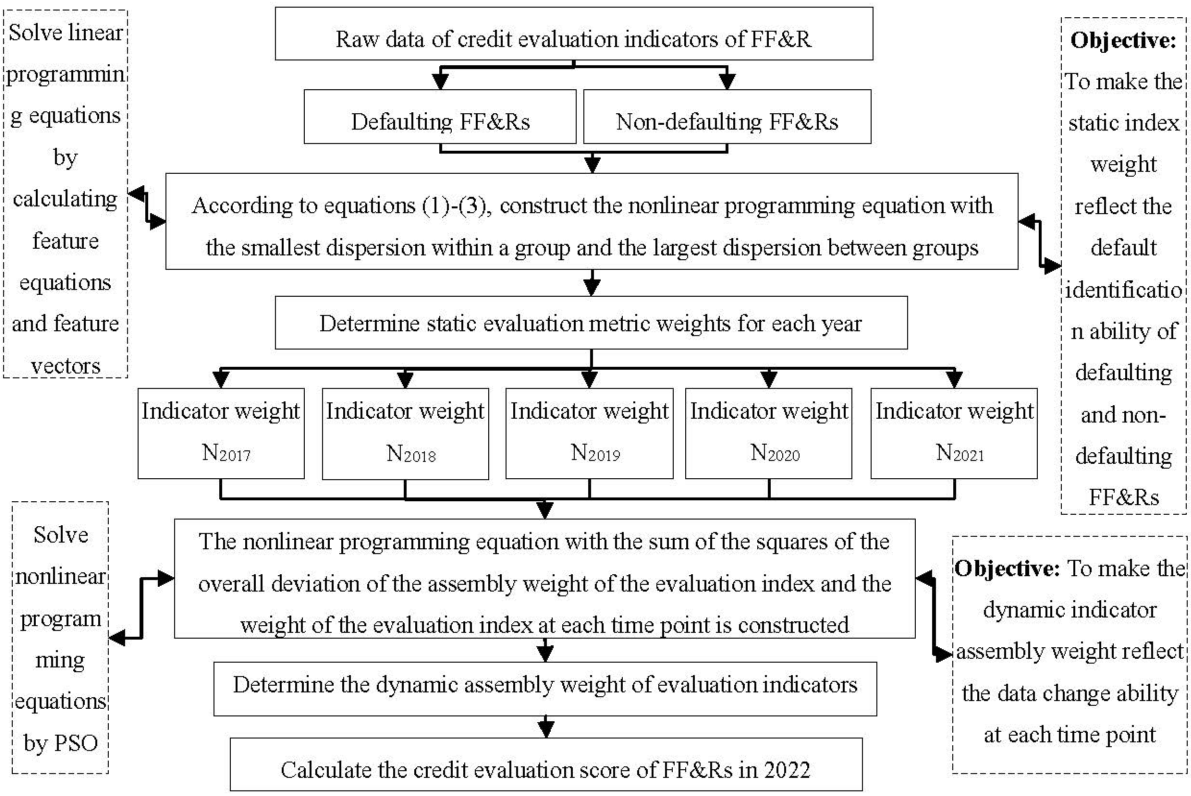

Fig. 1. Dynamic credit evaluation model from the perspective of weight set optimization and the technical route of application

3 Credit Evaluation Index Assignment and Evaluation Method

3.1 Fisher's Discriminant Method to Determine the Weight of Static Credit Evaluation Indexes

The idea of static assignment of credit evaluation indexes for FF&Rs is to divide the sample into two categories, default FF&Rs and non-default FF&Rs, and construct a nonlinear programming equation with maximum intra-class deviation and minimum inter-class deviation according to Fisher's discriminant idea to solve the credit evaluation index weights.

The steps of static assignment of credit evaluation indicators for FF&Rs are:

Step1: Solve for the intra-class deviation of defaulting FF&Rs, non-defaulting FF&Rs

Let: A=$(a_{ij})_{m*m}$- intra-class deviation matrix between credit evaluation indicators of FF&Rs; a_{ij}- intra-class deviation of the i-th indicator from the j-th indicator; n_1-number of non-defaulting FF&Rs; n_2-number of defaulting FF&Rs; $a_{ij}^{(1)}$-intra-class deviation of the i-th indicator from the j-th indicator among non-defaulting FF&Rs; $a_{ij}^{(2)}$-intra-class deviation of the i-th indicator from the j-th indicator among defaulting FF&Rs deviation; $\overline{x}_i$ -mean value of the i-th indicator; $\overline{x}_j$ -mean value of the j-th indicator; $\overline{x}_i^{(1)}$ -mean value of the i-th indicator in the non-defaulting FF&R; $\overline{x}_i^{(2)}$ -mean value of the i-th indicator in the non-defaulting FF&R. then [16]

$$\mathrm{a}_{ij} = \frac{n_1 * n_2}{n_1 + n_2}(\mathrm{a}_{ij}^{(1)} + \mathrm{a}_{ij}^{(2)}). \tag{1}$$

The economic meaning of equation (1) is that the intra-class deviation between FF&R credit evaluation indicators is the sum of the intra-class deviation of defaulted FF&R indicators and the intra-class deviation of non-defaulted FF&R indicators multiplied by a factor.

Step2: Solve for the inter-class deviation of defaulting FF&Rs, non-defaulting FF&Rs

Let: B=$(b_j)_{m*1}$-inter-class deviation matrix between default and non-default FF&R credit evaluation indicators; b_j-inter-class deviation of the j-th indicator default, non-default FF&R. Then [16]

$$b_j = n_1(\overline{x}_j^{(1)} - \overline{x}_j)^2 + n_2(\overline{x}_j^{(2)} - \overline{x}_j)^2. \tag{2}$$

The economics of equation (2) means that the inter-class deviation of the j-th indicator defaulted, non-defaulted FF&R is the sum of the deviation of the non-defaulted FF&R mean from the mean of all FF&Rs and the deviation of the defaulted FF&R mean from the mean of all FF&Rs.

Step3: Construct nonlinear programming equations by Fisher discriminant

Let: w-vector of indicator weight coefficients, w= (w_1, w_2, . . . , w_m), then the objective function is constructed with the intra-class deviation and inter-class deviation equations as constraints:

$$MaxF(w) = \frac{wBw^T}{wAw^T}. \tag{3}$$

The purpose of equation (3) is to find out the weight coefficients of FF&R credit evaluation indexes with the largest inter-class deviation and the smallest intra-class deviation.

Equation (3) features an assignment idea that it can reflect the idea that the greater the gap between defaulting FF&Rs and non-defaulting FF&Rs the greater the weight of the indicator.

Step4: Fisher's discriminant solves the static credit evaluation index weights of FF&Rs

Let: w_k*-the weight of static credit evaluation indicators of FF&Rs at the k-th time point, that is w_k*= (w_{k1*}, w_{k2*}, ... , w_{km*}), then

$$w_{kj}^* = \frac{w_{kj}}{\sum_{i=1}^{m} w_{ki}}. \tag{4}$$

The economic implication of equation (4) is to normalize the indicator weight coefficient vector w to obtain the static credit evaluation indicator weights for FF&R.

3.2 Particle Swarm Optimization Algorithm to Determine Dynamic Credit Evaluation Index Set Weights Method

The idea of measuring the dynamic aggregation weights of family farm credit evaluation indicators is to construct a nonlinear programming equation based on the known static FF&R credit evaluation indicator weights at multiple time points, and solve the equation by a particle swarm optimization algorithm to find the dynamic aggregation weights that deviate from the overall sum of squares of the weights at each time point to find the dynamic credit evaluation indicator weights that reflect the changing ability of the FF&R credit evaluation indicators at each time point. The dynamic credit evaluation index aggregation weights reflecting the ability to change the credit evaluation index data of FF&Rs at each time point are found.

The steps to measure the dynamic set weights of FF&R credit evaluation indicators are:

Step1: Construction of dynamic set weight measurement formula for credit evaluation indexes of FF&Rs

Let: D_j- dynamic set weights of the j-th FF&R credit evaluation index; c_k- time weight coefficients at the k-th time point, where k=1,2, ..., T; w_{kj}^*- static weights of the j-th FF&R credit evaluation index at the k-th time point. Then

$$D_{\mathrm{j}} = \sum_{k=1}^{T} \mathrm{c}_k * w_{kj}^{\ *}. \tag{5}$$

The economic meaning of equation (5) is to assign time weight coefficients to the static index weights of FF&R credit evaluation at each time point to obtain the dynamic set weights of FF&R credit evaluation indexes.

The innovation of equation (5) is that the dynamic set weights obtained by assigning time weight coefficients to the static weights of each time point can better reflect the change ability of indicator data at each time point, and the evaluation index weights obtained are more reliable.

Step2: Construct a nonlinear programming model to solve the dynamic set weights of FF&R credit evaluation indexes by the idea of overall deviation minimization

A nonlinear programming equation is constructed with the objective function of minimizing the sum of squared deviations of the FF&R credit evaluation weights from the FF&R credit evaluation index set weights at each time point and the constraint that the sum of the time weight coefficients at each time point is one. Then

$$\begin{cases} \min \sqrt{\sum_{k=1}^{T} (D_j - w_{kj}^{\ *})^2} \\ \sum_{k=1}^{5} a_k = 1 \ a_1, a_2, a_3, a_4, a_5 \in [0,1]. \end{cases} \tag{6}$$

The economic meaning of equation (6) is that the smaller the sum of the squared deviations of the dynamic set weights of credit evaluation of FF&Rs from the static credit evaluation index weights at each time point, then the more the dynamic set weights of the indexes can reflect the ability of data change, and the better the credit evaluation effect will be.

The innovation of equation (6) is to make up for the drawback that the traditional credit evaluation index assignment method cannot obtain the evaluation index weights reflecting the ability of data change at each time point.

The difference between equation (6) and the traditional weight measurement idea is that it makes up for the drawback that the data for the traditional weight measurement mostly comes from the original data of the evaluation index at a single time point in the process of being evaluated, resulting in the inability to accurately measure the importance of the evaluation index. In this paper, by constructing a nonlinear programming equation that minimizes the sum of the squared deviations of the index weights and the aggregated weights at each point in time, the dynamic aggregated weights that accurately reflect the ability of data change at each point in time are derived, which remedies the disadvantage that the traditional credit evaluation weight measurement method cannot obtain the evaluation index weights that reflect the ability of data change at multiple points in time by ignoring the continuity of time.

The difference between equation (6) and the traditional dynamic credit evaluation is that it makes up for the drawback that most traditional dynamic credit evaluations measure the credit evaluation scores of each time point and then linearly weight them with the time weights to get the final scores, without obtaining a set of dynamic evaluation index weights. In this paper, we construct a set of dynamic evaluation index weights that reflect the ability to change data at multiple points in time to facilitate the future credit score measurement.

Step3: Solve the nonlinear programming model using PSO algorithm

The main working principle of PSO is that the initial particles control the direction and speed of particle movement by adjusting the position of the particles and adjusting the speed of the particles to find the global optimal solution through continuous iteration. The PSO solves the nonlinear programming equation, and then obtains the dynamic set weights for the credit evaluation index of FF&Rs. the workflow diagram of PSO is shown in Fig. 2 [17].

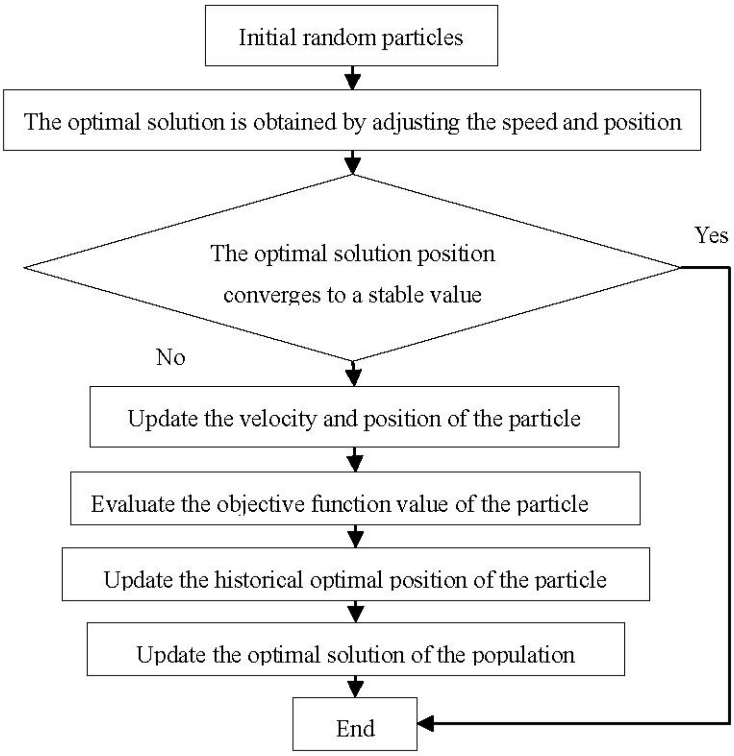

Fig. 2. Particle Swarm Optimization (PSO) algorithm flow

3.3 Linear Weighting Method for Solving FF&R Credit Evaluation Scoring Method

By measuring the dynamic set weights of FF&R credit evaluation indicators, the linear weighting method was used to solve the FF&R credit evaluation percentage score.

Let: F_j- the j-th FF&R credit evaluation percentage score; x_{ij}- the standardized credit evaluation score of the j-th indicator of the i-th FF&R; D_j-the dynamic set weight of the j-th FF&R credit evaluation indicator. Then

$$F_i = 100 * \sum_{j=1}^{m} x_{ij} * D_j . \tag{7}$$

The function of equation (7) is to calculate the FF&R credit evaluation percentage score, and a higher score indicates a higher credit level of the FF&R, and a lower score indicates a worse credit level of the FF&R.

4 Application Analysis

4.1 Sample Selection and Data Sources

Data were obtained from a questionnaire survey and in-depth telephone interviews with 100 Inner Mongolian FF&Rs for 6 years from 2017-2022, where 100 FF&Rs were mainly distributed in 12 leagues and cities in Inner Mongolia. Based on the principles of operability and observability, 11 evaluation indicators were selected with reference to previous literature, and the names of the indicators are listed in column 1 of Table 1. The types of indicators are divided into three categories: positive indicators, negative indicators, and qualitative indicators, which are listed in column 2 of Table 1. 100 original credit evaluation indicators data of FF&Rs from 2017-2022 are listed in columns 3-602 of Table 1. The first 16 of them are defaulted FF&Rs and the last 84 are non-defaulted FF&Rs.

Table 1. Raw and standardized data for family farm credit evaluation indicators 2017-2022

Serial number	(1) Indicator name	(2) Indicator type	Raw data for 2017			…	Raw data for 2022		
			(3) Sample1	…	(102) Sample100	…	(503) Sample1	…	(602) Sample100
1	X1Area of land in circulation/Total area of land operation	Positive	0.667	…	0.860	…	0.898	…	0.766
2	X2Annual turnover fee	Negative	886	…	3399		2749	…	58
3	X3Whether it is paid in time	Qualitative	Y	…	Y	…	Y	…	Y
4	X4Basic production facilities and the necessary number of mechanical equipment	Positive	4	…	4	…	5	…	8
5	X5Workforce population/Total household size	Positive	0.5	…	0.6667	…	0.5	…	0.5
6	X6Whether there are short-term employees	Qualitative	Y	…	Y	…	Y	…	Y
7	X7Number of perennial employees	Positive	2	…	0	…	0	…	2
8	X8Amount of funds	Positive	50	…	50	…	10	…	30
9	X9Whether there is an account opening license	Qualitative	Y	…	N	…	Y	…	Y
10	X10Asset value	Positive	70.7	…	136.5	…	45.5	…	385.3
11	X11Annual profit	Positive	69.5	…	96.0	…	27.1	…	121.1

4.2 Standardization of Indicators

As an example of raw data on credit evaluation indicators for FF&Rs in 2017:

Positive indicator standardization: the original data of positive indicators are listed in columns 3-102 of rows 1, 4, 5, 7, 8, 10, and 11 of Table 1, brought those into the positive indicator standardization formula to obtain the standardized data of indicators, and the results are included in columns 3, 6, 7, 9, 10, 12, and 13 of Table 3.

Negative indicator standardization: the original data of negative indicators are listed in in columns 3-102 of row 2 of Table 1, brought those into the negative indicator standardization formula to obtain the standardized data of other negative indicators, and the results are included in column 4 of Table 3.

Standardized scoring criteria for qualitative indicators: Based on rational analysis of qualitative indicators, we developed quantitative criteria for credit evaluation of FF&Rs and quantified qualitative indicators. X3, X6 and X9 are qualitative indicators for credit evaluation of FF&Rs, and the status of these three credit evaluation indicators is “Yes”, which means that the credit status of the FF&R is better, and the status of the credit evaluation indicators is “No”, which means that the credit status of the FF&R is worse. Therefore, the scoring guidelines shown in Table 2 were developed. The data in rows 3, 6 and 9 of Table 3 were scored according to the scoring criteria shown in Table 2, and the results were entered in columns 5, 8 and 11 of Table 3.

The same treatment was applied to the standardization of credit rating indicators for FF&Rs for 2018-2021.

Table 2. Guidelines for scoring qualitative indicators

Serial number	(1) Index	(2) State	(3) Score
1	X3Whether it is paid in time	Y	1.0000
		N	0.0000
2	X6Whether there are short-term employees	Y	1.0000
		N	0.0000
3	X9Whether there is an account opening license	Y	1.0000
		N	0.0000

Table 3. Standardized data on credit evaluation indicators for FF&Rs

Serial number	(1) Sample	(2) Default status	2017			…	2022			(69) Credit rating score
			(3) X1	…	(13) X11	…	(58) X1	…	(68) X11	
1	Sample 1	Defaulted	0.567	…	0.014	…	0.567	…	0.014	7.299
…	…		…	…	…	…	…	…	…	…
16	Sample 16		0.000	…	0.017	…	0.000	…	0.018	8.889
17	Sample 17	Non-defaulted	0.333	…	0.022	…	1.000	…	0.017	3.859
…	…		…	…	…	…	…	…	…	…
100	Sample 100		0.580	…	0.020	…	0.411	…	0.016	6.239

Table 4. Static weights of FF&R credit evaluation indicators and dynamic set weights

Serial number	(1) Indicator name	(2) w_{2017}	(3) w_{2018}	(4) w_{2019}	(5) w_{2020}	(6) w_{2021}	(7) W^*_{2017}	(8) W^*_{2018}	(9) W^*_{2019}	(10) W^*_{2020}	(11) W^*_{2021}	(12) D
1	X1	0.0089	0.0295	0.0305	0.0297	0.0046	0.0037	0.0325	0.0125	0.0156	0.0022	0.0130
…	…	…	…	…	…	…	…	…	…	…	…	…
5	X5	0.1197	0.1189	0.0549	0.0493	0.0431	0.0497	0.1310	0.0226	0.0259	0.0212	0.0485
…	…	…	…	…	…	…	…	…	…	…	…	…
11	X11	0.0951	0.1006	0.1146	0.0580	0.0291	0.0395	0.1108	0.0471	0.0304	0.0143	0.0470

4.3 Fisher's Discriminant Method to Determine the Weights of Static Credit Evaluation Indexes

Step1: Rows 1-16 of Table 3 show defaulting FF&Rs, and columns 17-100 show non-defaulting FF&Rs. Taking the 2017 credit evaluation index data of FF&Rs as an example, which is the data from rows 1-100 and columns 3-13 of Table 3, it is evident that n1=84 and n2=16. By bringing the data into formula (1), the intra class dispersion matrix between credit evaluation indicators of FF&Rs can be obtained, then

$$A=\left(a_{ij}\right)_{11*11}=\begin{pmatrix}126.587 & \dots & -4.748\\ \vdots & \ddots & \vdots\\ -4.748 & \cdots & 14.603\end{pmatrix}$$

The data on the credit evaluation indicators of FF&Rs for 2018-2021, that is, the same data in columns 14-57 of Table 3, allow to derive the intra-class deviation matrix between the credit evaluation indicators of FF&Rs for 2018-2021.

Step2: Using the 2017 FF&R credit evaluation index data as an example, that is, the data in columns 3-13 of rows 1-100 in Table 3, the data can be brought into formula (2) to find the inter-class deviation matrix between default and non-default FF&R credit evaluation indexes, then

$$B = \left(b_j\right)_{11*1} = \left(0.040, ..., 0.025\right)$$

The data on the credit evaluation indicators of FF&Rs for 2018-2021, that is, the same data in columns 14-57 of Table 3, allow to derive the inter-class deviation matrix between the credit evaluation indicators of defaulted and non-defaulted FF&Rs for 2018-2021.

Step3: Taking the 2017 FF&R credit evaluation index data as an example, the indicator weight coefficient vector w, the intra-class deviation matrix A between FF&R credit evaluation indexes and the inter-class deviation matrix B between default and non-default FF&R credit evaluation indexes can be calculated by bringing the indicator weight coefficient w into equation (3), and the results are included in column 2 of Table 4.

The same weighting coefficients for the credit evaluation indicators of FF&Rs in 2018-2021 were used, and the results were included in columns 3-6 of Table 4.

Step4: Taking the credit evaluation index data of FF&Rs in 2017 as an example, the weight coefficients of credit evaluation indexes of FF&Rs, i.e., the data in column 2 of Table 4, were brought into formula (4) to obtain the weights of credit evaluation indexes with default identification ability under Fisher's discriminant method, and the results were included in column 7 of Table 4.

The same weighting was applied to the credit evaluation indicators of FF&Rs for 2018-2021, and the results were included in columns 8-11 of Table 4.

4.4 Aggregate Weight Measurement and Credit Evaluation Score

The data in columns 7-11 of Table 4 were brought into equations (5)-(6) to solve for the dynamic set weights of FF&R credit evaluation indicators, and the results were calculated by software to derive the time weights of FF&R credit evaluation, and the results were included in Table 5 to derive the dynamic set weights of FF&R credit evaluation indicators, and the results were included in column 12 of Table 4.

Table 5. Time weighting coefficients for the solution of the PSO algorithm

Year	2017	2018	2019	2020	2021
Coefficient	0.20485	0.20331	0.18544	0.2008	0.1137

4.5 The Linear Weighting Method Solves the Credit Evaluation Score of FF&R

The data in columns 503-602 of Table 1 and column 12 of Table 4 were brought into equation (7) to obtain the FF&Rs credit evaluation percentage score, and the results were included in column 69 of Table 3.

5 Conclusion

5.1 Main Conclusions

The static weights of credit evaluation indexes of 100 FF&Rs in 2016-2021 were measured by Fisher's discriminant method, respectively. Based on the PSO algorithm to measure the dynamic set weights of credit evaluation indexes of FF&Rs in 2016-2021, the dynamic set weights of 11 credit evaluation indexes were measured as D= (0.0130, 0.0339, . . . , 0.0470), and based on these weights and the data of credit evaluation indexes in 2022, we measured the 100 FF&Rs credit evaluation scores in 2022.

5.2 Major Innovations

In this paper, by constructing a nonlinear programming equation with the minimum sum of squared deviations of index weights and aggregation weights at each time point, we find out the dynamic aggregation weights that accurately reflect the change ability of data at each time point, and make up for the drawback that the traditional credit evaluation weight measurement method cannot obtain the evaluation index weights that reflect the change ability of data at multiple time points by ignoring the time continuity.

6 Acknowledgments

The research was supported by the National Natural Science Foundation of China (72161033), the Inner Mongolia Institute for Rural Development of China and Inner Mongolia Autonomous Region Graduate Scientific Research Innovation Project of China (S20231116Z).

References

[1] G.-Z. Zhang, Z. Xu, Y. Lan, Research on evaluation index system of family farm based on AHP method, Journal of Central South University of Forestry and Technology 37(7)(2017) 136-139.

[2] Z.-J. Pan, X. Huang, Choice and Cultivation of Management Subjects for New Agriculture——a Case Study of Yongzhou City, Hunan Province as an example, Journal of South-Central University for Nationalities (Humanities and Social Sciences Edition) 39(4)(2019) 132-137.

[3] J.-F. Yuan, W. Li, B. Xia, Y. Chen, M.-J. Skibniewski, Operation performance measurement of public rental housing delivery by PPPS with fuzzy-AHP comprehensive evaluation, International Journal of Strategic Property Management 23(5)(2019) 328-353.

[4] Y. Lan, Y.-P. Zhou, M. Jiang, The comprehensive evaluation of the benefit linkage mechanism between family farms and agricultural enterprises, Research of agricultural modernization 42(5)(2021) 805-814.

[5] J.-H. Xu, N.-Q. Wang, F.-L. Guo, Construction and Demonstration of the Evaluation Index System for the Development Level of Digital Countryside, Statistics and Decision 39(2)(2023) 73-77. DOI: 10.13546/j.cnki.tjyjc.2023.02.014

[6] Y.-J. Guo, Y. Yao, P.-T. Yi, A Method and Application of Dynamic Comprehensive Evaluation, Systems Engineering-Theory and Practice 27(10)(2007) 154-158.

[7] B.-F. Shi, B. Meng, J. Wang, Dynamic Empowerment Method Based on Matrix Distance Revised Topsis, Systems Engineering 33(3)(2015) 137-142.

[8] F.-M. Zhang, W.-M. Wang, X.-S. Li, Enterprise Dynamic Credit Revaluation Method Based on TOPSIS-GRA and Its Application, Operations Research and Management Science 27(9)(2018) 132-138.

[9] Y.-Y. Yang, J.-C. Feng, Y.-Q. Huang, M. Li, S. Xue, L.-B. Wang, K. Zhang, Research on the Comprehensive Credit Dynamic Evaluation Model of the Construction Market: Taking Construction Enterprises as an Example, Science and Technology Management Research 38(18)(2018) 57-66.

[10] J.-C, Feng, Y.-C. Wang, H. Feng, M. Li, S. Xue, Research on the Comprehensive Dynamic Evaluation Model of Enterprise Credit under PPP Mode, Soft Science 33(3)(2019) 49-53+79.

[11] L.-B. Zhang, C.-G. Zhou, M. Ma, X.-H. Liu, Solutions of Multi-Objective Optimization Problems Based on Particle Swarm Optimization, Journal of Computer Research and Development 47(7)(2004) 1286-1291.

[12] F.-F. Feng, X.-L. Wu, R.-Q. Niu, S.-L. Xu, X.-Y. Yu, Landslide susceptibility assessment based on PSO-BP neural network, Science of Surveying and Mapping 42(10)(2017) 170-175.

[13] F.-Q. Wu, Y.-J. Xu, Construction and Verification of Regional Collaborative Innovation Capability Prediction Model Based on Particle Swarm Optimization, Statistics and Decision 34(23)(2018) 44-48.

[14] X.-J. Ma, B.-Y. Dong, C.-X. Wang, Design of a Credit Rating Model of Quoted Companies Based on the PSO Optimized Weighted Random Forest Algorithm, The Journal of Quantitative and Technical Economics 36(12)(2019) 165-182.

[15] R.-Q. Yan, T. Wang, X.-Y. Jiang, Q.-F. Zhong, X.-Z. Yue, Design of high-performance plasmonic nanosensors by particle swarm optimization algorithm combined with machine learning, Nanotechnology 31(37)(2020) 1-21.

[16] B.-F. Shi, Credit Rating Model Based on Default Pyramid Principle: Empirical Evidence from Chinese Small Enterprises, Dalian University of Technology 2014.

[17] S. Li, L.-J. Liu, M. Zhai, Prediction for short-term traffic flow based on modified PSO optimized BP neural network, Systems Engineering-Theory and Practice 32(9)(2012) 2045-2049.