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The Study of Prediction Model of Enterprises' Operating Performance by Using Fruit Fly Optimization Algorithm

Taking Intelligent Technology Industry in China for Example

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***Abstract*—With the unveiling of the "Made in China 2025" plan, the future of manufacturing has been transformed from "made in China" to "intelligent manufacturing in China" and it means that the new era of intelligent technology has come. However, there is still not a specific and effective model for predicting enterprises' operating performance because the development of intelligent technology industry in China started late. Therefore, this study applies fruit fly optimization algorithm to optimize multiple regression and construct the most appropriate model which can effectively predict the enterprises' operating performance of intelligent technology industry in China. The result shows it has good ability to optimize multiple regression by fruit fly optimization algorithm and obviously enhance the prediction performance.**

Keywords—Fruit fly optimization algorithm; Big data; Intelligent technology; Operating performance; Prediction model

I. INTRODUCTION

In recent years, the intelligent technology industry has been developing vigorously and the global intelligent technology companies are more actively engaged in developing emerging applications. In 2015, the Chinese government issued the "Made in China 2025" plan, emphasizing the realization of the intelligent technology transformation. On the other hand, it has actively attracted investment at home and abroad, and has also accelerated the promotion of research and practice of intelligent manufacturing. The Ministry of Industry and Information Technology of China has launched intelligent manufacturing projects for 38 related industries in China and 46 countries in 21 regions of the world. The market capacity of the whole Chinese intelligent manufacturing industry has reached US$16.6 billion, and according to the industry research report of iResearch, the sales of the most popular categories of intelligent hardware in China have reached more than US$1.66 million in 2015. In 2016, the scale of Chinses intelligent industry reached US$1.6 billion, an increase of 37.9% over the same period in 2015, which will continue to grow [1]. The operating revenues from the intelligent technology industry are increasing substantially year by year in China, however, the enterprise operating system of intelligent technology industry in China is still not perfect than Euramerican developed country. It is worth noting that under the high-speed development of intelligent technology industry, enterprises might not have refined operating system, and therefore they might easily lose control over the cost and quality of their production. As a result, this study attempts to construct an appropriate prediction model of enterprises' operating performance for intelligent technology industry in China.

With the development of Internet and big data technology, more and more swarm intelligence algorithms have been proposed. The Fruit Fly Optimization Algorithm (FOA) is a new swarm intelligent optimization algorithm propose by Pan in 2011 and has been widely proved to improve the predictive power of models. Moreover, compared with the other optimization algorithms, FOA has less calculation, lower complexity, higher optimization precision, and stronger applicability [2−4]. Therefore, this study attempts to improve the predictive power of the operating performance model using FOA and find the important indexes to model as well. The result would be the reference for the operating performance prediction of intelligent technology industry in China.

II. LITERATURE REVIEW

Szilagyi and Wallace (1990) suggested that operating performance can help to guide an organization to rationally distribute its future resources [5]. Among intelligence intensive and technology intensive enterprises, the indicators often used to measure operating performance include earnings per share [6], Tobin 's Q and return on asset [7], return on equity [8], and

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so on. In addition, the operating performance is usually influenced by many factors. In the field of high-tech industry, many scholars find that the important factors to operating performance are basically covered by intellectual capital, including the total asset turnover ratio, the inventory turnover ratio, the fixed assets turnover ratio, investment of R&D and intensity of R&D and so on [9].

As mentioned above, FOA has been widely applied in many fields. For example, in financial field, it was used in optimizing generalized regression neural network model to improve the prediction precision [10]. In addition, it was conducted successfully in power load forecasting [11], fund trading decision prediction [12], and auto parts sales forecast [13]. However, FOA is rarely use in predicting intelligent technology enterprises' performance in China. Therefore, this study optimizes the parameters of multiple regression model using FOA, and to construct an effectively prediction model of operating performance for intelligent technology enterprises in China.

III. Research Design

A. Research Process

This study serves for the national development goal and focuses on the intelligent technology industry. Based on the understanding of the current situation of the development of the industry, as well as an overview of relevant literature, the conceptual framework for this research is built. Also, the obtained raw data of intelligent technology enterprises for this study is cleaned. Then, the multiple regression (Regression) and the multiple regression optimized by FOA (FOA-Regression) are constructed and compared. Finally, the appropriate prediction model is found in this study and the future operation strategies are put forward as reference (as shown in Fig. 1).

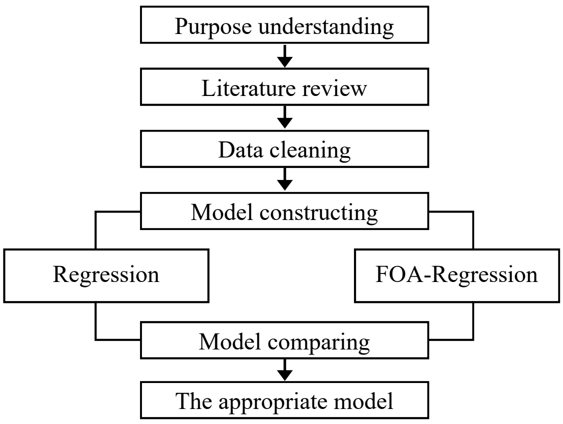

Fig. 1. The figure of research process.

B. Data and variables

The research objective of this study is to build an operating performance prediction model for intelligent technology industry in China, and the data is obtained through the CSMAR database including 2,554 samples from 2006-2016.

There are 4 dependent variables in this study, return on asset (ROA), return on equity (ROE), Tobin's Q, and earning per share (EPS) [14-16], which are often used to measure operating performance of enterprises. In terms of independent variables (IV), as intelligent technology enterprises are knowledge and technology intensive, R&D activities and costs will affect the development of future products and the provision of technical services, which will have a far-reaching impact on the overall operation of the enterprise. Therefore, this study first identifies R&D related indicators as important factors, including R&D expenditure (RDE), and R&D productivity (RDP). According to the previous studies, accounts receivable turnover ratio (ARTR), inventory turnover ratio (ITR), fixed assets turnover ratio (FATR), total assets turnover ratio (TATR), liquid assets turnover ratio (LATR), net income ratio (NTR) and management expenditure rate (MER) are also used as the input variables of the model [17].

C. The Fruit Fly Optimization Algorithm

The fruit fly is superior to other species in sensory perception, especially in the sense of smell, the stronger the smell of the food, the more the fruit fly can perceive. The perceived smell concentration by fruit fly is related to the distance between the fruit fly and food. The farther away the distance, the weaker the odor concentration will be perceived. The process of fruit flies finding an object is the process of constantly reaching from a lighter-smell place to a more concentrated smell place. For example, three of the fruit flies fly in random directions from the initial position of the fruit fly group, and later, all the flies fly to the fruit flies that perceive the highest concentration of odour, forming a new population of flies, and then fly out again, and continue to repeat the cycle until they find the food source.

According to the characteristics of fruit fly searching for food, the specific steps of the algorithm are as follows [10]:

1) Random initial position of fly group (Fly Group).

$$InitX\_axis;\ InitY\_axis \tag{1}$$

2) Giving the individual fly (Fly1, Fly2, Fly3) the random direction and distance to search for food using the sense of smell.

$$Xi = X\_axis + Random\ Vlaue \tag{2}$$

$$Yi = Y\_axis + Random\ Vlaue \tag{3}$$

3) Since the position of the food cannot be known, the distance (Dist) from the initial position is estimated first, and then the determination value of smell concentration (S) is calculated, which is 1 divided by the distance.

$$Dist_i = Sqrt(X_i^2 + Y_i^2) \tag{4}$$

$$S_i = 1 / Dist_i \tag{5}$$

4) The smell concentration determination value (S) is substituted into to a smell concentration determination function (Fitness function) to obtain the smell concentration of the individual position of the fruit fly (Smelli).

$$Smell_i = Function(S_i) \quad (6)$$

5) Finding the fruit fly at the strongest smell concentration position out of the whole fly group (Find the maximum, such as Fly2).

$$[best\ Smell\ best\ Index] = max(Smell) \quad (7)$$

6) Keeping the strongest smell concentration values and the x, y coordinates of that location, where the fruit fly group using the sights to fly to and form a new cluster location (Fly2).

$$X\_axis = X(best\ index) \quad (8)$$

$$Y\_axis = Y(best\ index) \quad (9)$$

7) By repeating steps 2-5, and determine if the smell concentration is stronger than the smell concentration in the previous iteration taste concentration. If yes, go to step 6.

$$Smell\ best = best\ Smell \quad (10)$$

IV. Empirical Analysis

A. Important Factors to Operating Performance

In this study, ROA, ROE, Tobin's Q, and EPS are respectively taken as the measurement for operating performance (dependent variable), and independent variables are selected by stepwise regression to build prediction model. The results of 4 models are shown in Table I.

TABLE I. THE RESULTS OF OPERATING PERFORMANCE PREDICTION MODELS

Model	IV	Beta	P-value	VIF	RMSE
ROA	FATR	-0.064	0.001	1.033	0.98874
	TATR	0.274	0.000	1.023	
	RDP	0.040	0.037	1.012	
ROE	FATR	-0.040	0.045	1.033	0.99109
	TATR	0.172	0.000	1.023	
	RDP	0.112	0.000	1.012	
Tobin's Q	ITR	0.047	0.000	1.002	5.87143
	FATR	-0.042	0.017	1.023	
	TATR	-0.108	0.036	1.029	
	RDE	-0.085	0.000	1.008	
EPS	ARTR	0.104	0.000	1.002	0.96299
	FATR	-0.064	0.001	1.034	
	TATR	0.278	0.000	1.030	
	RDE	0.135	0.000	1.009	
	RDP	0.059	0.002	1.013	

From Table I, no matter which measurement (dependent variable) is used for enterprise's operating performance, the important factors selected by each model basically include FATR, TATR and RDP. Obviously, these three are the important variables that affect the performance of intelligent technology enterprises.

B. Operating Performance Optimization Model

This study uses FOA to optimize the coefficients of four regression models as above respectively. The initial settings are all 5 fly groups. The randomly initial range (IR) is [0, 1] (see (1)). The iterated fly searching for food has a random direction and distance (RDD) of [-1, 1] (see (2) & (3)). The maximum number of iteration was 100. According to (4) to (10), the optimal coefficients of regression models of ROA, ROE, Tobin's Q and EPS were obtained through 100 iterations, and the prediction results of the model also gradually approached the target value. The optimization results by FOA are shown in Table II.

TABLE II. THE OPTIMIZATION RESULTS BY FOA-REGRESSION

model	ROA	ROE	Tobin's Q	EPS
Iteration	35	37	12	17
RMSE	0.00216	0.00171	0.11647	0.00553
Optimal coefficients				
FATR	0.03928	0.03928	0.04854	0.03674
TATR	0.03774	0.03774	0.05052	0.03774
RDP	0.03853	0.03853	-	0.03770
RDE	-	-	0.04796	0.03631
ARTR	-	-	-	0.03610
ITR	-	-	0.04732	-

Table II shows the FOA-ROA model converged in the 35th iteration, the RMSE value was 0.00216, and the best model parameters were 0.03928, 0.03774, 0.03853. The FOA-ROE model converged in the 37th iteration, the RMSE value was 0.00171, and the best model parameters were 0.03928, 0.03774, 0.03853. The FOA-Tobin's Q model converged in the 12th iteration, the RMSE value was 0.11647, the best model parameters were 0.04854, 0.05052, 0.04796, 0.04732 and the FOA-EPS model converged in the 17th iteration, and the RMSE value was 0.00553.

C. Model Comparison

This study compares the RMSE values of all Regression models and FOA-Regression models. From Table III, it can be found that the RMSE values of the FOA-Regression models are significantly smaller than those of the Regression models. The FOA-optimized regression model has smaller prediction error and stronger predictive power. In addition, among all the FOA-Regression models, the regression model with ROE as the measurement variable of operating performance has the smallest RMSE value and the best prediction effect. Therefore, the FOA- ROE model is the most appropriate model for predicting the enterprises' operating performance of intelligent technology industry in China. In this model, the variables which have an important impact on the enterprise are FATR, TATR and RDP.

TABLE III. THE COMPARISON OF TWO MODELS

Model		Regression	FOA-Regression
RMSE	ROA	0.98874	0.00216
	ROE	0.99109	0.00171
	Tobin's Q	5.87143	0.11647
	EPS	0.96299	0.00553

V. Conclusion

In recent years, intelligent technology industry in China has developed rapidly, but at the same time, it is more prone to operation problems. There are no specific applicable indicators or models to help companies to predict operating performance and provide appropriate operational guidance for this newly emerging industry. Today, in the era of big data, a lot of data about the operating status of enterprises can be used to explore more enterprise information. Therefore, this study optimizes the prediction model of operating performance by FOA, and finds the most appropriate model for intelligent technology enterprises in China. The results show that FOA greatly improves the predicting ability of enterprise operating performance model, and the prediction error of the model optimized by FOA is significantly reduced. Therefore, the most appropriate model and important factors to the operating performance prediction of intelligent technology enterprises in China are also determined.

For intelligent technology enterprises in China, among the variables affecting their performance, fixed assets turnover ratio, total assets turnover ratio and R&D productivity are the most important factors selected by the model, which have a significant positive influence to the operating performance. Compared with the general enterprise, the fixed assets of intelligence technology enterprises are mostly used for precise experiment, measurement and analysis. Also, the value of these fixed assets is very high and they are critical for the scientific and technological research and development. Whether the fixed assets can be reasonably maintained and utilized affects the output of scientific research results. Therefore, enterprises should form a scientific fixed asset management system, define the management department and the principle of division of labour and keep fixed assets at a longer operating life and better performance, so that they can provide the best working environment for the enterprise's technology research and development, and create greater enterprise value. In addition, enterprises should also establish a scientific budget and investment analysis system to make the optimal acquisition of fixed assets. For assets projects with greater risks, they should be more cautious and can adopt methods such as external leasing to minimize waste of resources and increase the efficiency of asset utilization.

Whether intelligent technology enterprises can realize the development of their unique intelligent technologies and products is also the core competitiveness of enterprises. Therefore, intelligent technology enterprises should focus on R&D, planning ahead for R&D, and avoiding unreasonable R&D investment. At the same time, companies should strengthen the cooperation within their internal departments or with external material suppliers to achieve mutual complementary resources and improve the quality and efficiency of research and development. However, the success of intelligent technology enterprises depends not only on R&D activities and the operation of fixed assets. Enterprises should pay more attention to the effective management of their overall resources. With the development of enterprise management informationization, various enterprise information management software, systems and platforms have emerged. Therefore, intelligent technology enterprises can introduce or design refined management systems, such as ERP system and financial management system, to improve the scientific analysis and management of assets, which in turn improves the efficiency of deploying assets in generating revenue and also overall operating performance.

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