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Research Article

Modelling Enterprise's Coordinated Development Strategy with a Soft Fuzzy Rough Set

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With the concept of sustainable development, enterprises are facing severe challenges in ecological protection and economic development. Approaches to improving effectiveness of the coordinated development strategy must continue to evolve to address uncertainty and hazards that may be encountered in the future. We propose a coordinated development strategy model based on the combination of soft fuzzy and rough set theory and construct its prediction model. For the multistrategy dataset in the paper, parameter for each kind shall be selected through converting the multistrategy data into two prediction datasets. An algorithm transformed by SFRC shall be subject to weighted average for each parameter. Furthermore, we use training methods and soft fuzzy rough sets' learning algorithm to calculate, and the evaluating indicator rough set is constructed with a three-tier model structure. After the final rough set training is completed, test results show that the rough set model which has a higher rating accuracy builds a better completed business performance evaluation. By comparing the prediction effect, both SVM algorithm and multistrategy prediction model for the soft fuzzy rough set in the paper can realize effective prediction for the enterprise's coordinated development strategy. Moreover, the prediction result obtained at the time of adopting boundary to get the expected value is superior to that of giving one fixed threshold. It shows that the prediction performance of the algorithm in the paper is more excellent and represents the advantage of the algorithm prediction performance at the time of adopting boundary to get the expected value. The model provides support methods to assist enterprise management in making more efficient and scientific decisions for enterprise's coordinated development.

1. Introduction

An American scientist Rachel Carson warned the world in the famous book "*Silent Spring*." Regrettably, more than 40 years have passed, and the environmental problems Carson worried about did not disappear from the world. Instead, they became more serious. The environmental problems faced by mankind have evolved into local, small-scale, regional, and even global issues. The Chinese government has elevated ecological protection to a basic national policy and implemented strict laws to promote the country's green development and lifestyle. Companies that rely on high energy consumption and high emissions must change their development strategy and participate in the government and society's cogovernance system while pursuing profits. Social responsibility mechanism for the enterprise shall be improved to realize coordinated development and ecological environment.

Rough set theory [1] is concerned with vagueness and granularity in terms of approximations [2]. To date, the theory has been applied in many research fields, including knowledge discovery, pattern recognition, information processing, granular computing, and data analysis [3–7]. In recent years, many researchers have established generalized rough set models, e.g., rough fuzzy set and fuzzy rough set models, neighborhood rough sets, probabilistic rough sets, rough sets for decision theory, soft rough sets, and general binary relations [8–10]. These universal rough set models are used to handle roughness and vagueness in a precise way. Different researchers have pointed out that the main disadvantages of the classical knowledge representation model lie in its sensitivity to data noise. A new FRS model is able to

manage noise influence in some classification assignments [11].

Multiple-criteria decision-making methods have appeared in the last decade [12]. In order to improve effectiveness for coordinated development strategy research of enterprises in view of concepts of social responsibility and ecological environment protection, we propose one kind of research strategy based on the soft fuzzy rough set and construct the growth curve prediction model, and the effect is predicted by taking advantage of the soft fuzzy rough set model to obtain group of strategy prediction set for each coordinated development strategy.

2. Mathematical Model for Economic Analysis

2.1. Growth Curve Prediction Model. For the coordinated development strategy of enterprises, the growth curve model can be utilized for construction, and the growth curve model is one kind of curve to describe the growth process for creatures originally. It is found through observation that speed for the growth process of many things changes slowly and then gradually speeds up. After it reaches the quickest growth speed, it starts to slow down again. Finally, its growth speed is nearly approximate to the dead state to reach some extreme.

In case $\mathrm{d}y/\mathrm{d}t$ presents growth speed for variable y, its growth curve can be described in the following differential equation:

$$\frac{\mathrm{d}y}{\mathrm{d}t} = (a - by)y. \tag{1}$$

This is one nonlinear ordinary differential equation. Supposing its initial value $y = y_0$ at time $t = 0$, appropriate parameter substitution can be conducted. Supposing $k = a/b$ and $m = (k - y_0)/y_0$, the following can be obtained:

$$y = \frac{k}{\left(1 + me^{-at}\right)}. \tag{2}$$

This equation is the logistic curve equation, and k, m, and a are undetermined coefficients. They can be confirmed by taking advantage of curve fitting through the historical data sequence of y, and in the future, the y value can be predicted through equation (2).

2.2. GM (1, 1) Model for Grey Prediction. Grey system refers to a system with incomplete and inaccurate information to be used as grey prediction, and the GM (1, 1) model is the most frequently used. It is a model for the first-order grey differential equation of 1 variable. Variable set $X^{(0)}$ shall be considered:

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\right\}. \tag{3}$$

Its corresponding differential model is

$$\frac{\mathrm{d}X^{(1)}}{\mathrm{d}t} + aX^{(1)} = u, \tag{4}$$

where a is the equation coefficient and u is the endogenous variable; and they are both pending parameters. They are recorded as $\widehat{a} = \{a, u\}^T$; $X^{(1)}(i) = \sum_{k=1}^{i} X^{(0)}(k)$ is 1 time growth sequence of original sequence $X^{(0)}$, and it is recorded as

$$Z^{(1)}(k+1)^{(k=1)} = \left(\frac{X^{(1)}(k+1) + X^{(1)}(k)}{2}\right). \tag{5}$$

Through mathematical derivation, the calculation equation for the following pending parameter that needs to be calculated can be obtained:

$$\widehat{a} = \left(B^T B\right)^{-1} B^T Y_N, \tag{6}$$

where expressions for B and Y_N are shown in [13]. After calculation for $\widehat{a} = \{a, u\}^T$ by taking advantage of equation (5), there is one model:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = u. \tag{7}$$

And the sequence for generating the model is

$$\widehat{x}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{u}{a}\right)e^{(-ak)} + \frac{u}{a}. \tag{8}$$

Through the sequence of equation (7), reduction sequence $\widehat{x}^{(0)}(k), k = 2, 3, \ldots, n, \ldots$, taken as the prediction result, can be obtained. Thus, the purpose of conducting a variable value in follow-up time by taking advantage of the GM (1, 1) prediction model through sequence $\widehat{x}^{(0)}(m), m = 1, 2, \ldots, n$, can be reached. It can be known from equation (7) that e^{-ak} item is for time k. When the sequence that needs to be predicted changes according to the index law, the GM (1, 1) model has relatively high prediction accuracy.

3. Soft Fuzzy Rough Set Model

3.1. Soft Fuzzy Rough Set. Thinking of selecting soft threshold in the soft margin, SVM is introduced into fuzzy rough set theory, and one kind of concept different from soft distance for the recent distance method of the original calculation sample is proposed.

Definition 1. Given one sample practice x and one sample entity set $Y = \{y_1, y_2, \ldots, y_n\}$, soft distance between x and Y is defined as follows:

$$\mathrm{SD}(x, Y) = \arg\max_i \{d(x, y_i) - C \times m_i\}, \quad y_i \in Y, i = 1, 2, \ldots, n, \tag{9}$$

where $d(x, y_j)$ is the distance function between x and y_j, C is the penalty factor, and m_i is the sample quantity meeting condition of $d(x, y_j) < d(x, y_i)$, $j = 1, 2, \ldots, n$.

One example of confirming soft distance is given in Figure 1. Supposing sample x belongs to kind 1 and other samples belong to kind 2, Y shall be used to express this sample set. In case y_1 is taken as one noise sample and is ignored, SD(x, Y) shall be d_2. Therefore, one penalty item is needed to judge whether how many samples shall be

ignored. In case one sample is ignored, C will be deducted for $d(x, y_j)$. For all candidate distances $d(x, y_j)$, $d(x, y_k) = \text{argmax}_i\{d(x, y_i) - C \times m_i\}$ shall be taken as soft distance between x and Y. That is, distance $d'(x, y_j)$ is the maximum after punishing all ignored samples. This is about selection for parameter C.

On the basis of soft distances shown in Figure 1, soft fuzzy rough set is defined as follows.

Definition 2. Taking U as one nontheoretical domain, R is one fuzzy equivalence relation on U. $F(U)$ is the fuzzy power set of U. The soft fuzzy upper and lower approximation for $F \in F(U)$ can be defined as

$$\begin{cases} \underline{R}^S F(x) = 1 - R\left(x, \arg \sup_{y \; F(y) \le F(y_L)} \{1 - R(x, y) - C \times m\}\right), \\ \overline{R}^S F(x) = R\left(x, \arg \sup_{y \; F(y) \ge F(y_U)} \{1 - R(x, y) + C \times n\}\right), \end{cases} \tag{10}$$

where

$$\begin{cases} y_L = \arg \inf_{y \; y \in U} \max\{1 - R(x, y), F(y)\}, \\ y_U = \arg \sup_{y \; y \in U} \min\{R(x, y), F(y)\}. \end{cases} \tag{11}$$

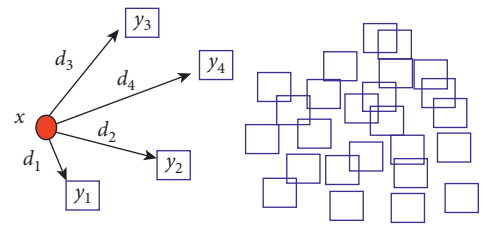

Figure 1: Schematic diagram for soft distance.

C is one penalty factor, and m is the quantity for the ignored sample at the time of calculating $\underline{R}^S F(x)$. N is the quantity for the ignored sample at the time of calculating $\overline{R}^S F(x)$. In case set A is one clear set, the membership degree of sample x to the soft fuzzy lower approximation is expressed as follows:

$$\underline{R}^S A(x) = 1 - R(x, y_{\text{AL}}), \tag{12}$$

where

$$\begin{aligned} y_{\text{AL}} &= \arg \sup_{y \; A(y)=0} \{1 - R(x, y) - C \times m\} = \arg \sup_{y \; A(y)=0} \{d(x, y) - C \times m\} \\ &= \arg_y \text{SD}(x, U - A). \end{aligned} \tag{13}$$

$\underline{R}^S A(x)$ is equal to soft distance between sample x and $U - A$.

3.2. Soft Fuzzy Rough Predictor. Hu et al. designed one robust predictor on the basis of the lower approximation definition for the above soft fuzzy which can be used to solve single-strategy prediction [13]. Its principle can be summarized as follows: the value of one sample needs to be predicted and membership degree of the soft fuzzy lower approximation in every kind shall be calculated. A training sample set with k kinds and one sample c that needs to be predicted shall be given. Firstly, supposing x belongs to every kind, the value of sample x to the membership value for the soft fuzzy lower approximation of k kind shall be calculated, and x shall be predicted to the effect of the maximum membership degree. It can be expressed in the following equation:

$$\text{class}_i(x) = \arg \max_{1 \le j \le k} \left\{\underline{R}^S \text{class}_j(x)\right\}. \tag{14}$$

$\underline{R}^S \text{class}_i(x)$ is the membership degree of x to the soft fuzzy lower approximation of kind class_i Algorithm 1.

The algorithm is described as follows:

3.3. Parameter Setting. It can be seen from Figure 2 in Section 4.1 that the value for penalty factor C in the soft fuzzy rough set has important significance on its robustness. One method for parameter setting is shown in [13].

Taking one sample x, for example, credibility f for the soft superball that is subject to the sample as the ball center shall be given. At the time of calculating credibility for the soft superball that is subject to x as the ball center, in case its value is more than or equal to f, the difference between the radius of the soft superball and the hard superball is greater than that of few different samples in the soft superball, and specific C value is obtained when taking sample x as the ball center. At the same time, credibility for the soft fuzzy lower approximation is guaranteed. For one dataset containing n samples, the calculated C average value that is subject to each sample as the ball center shall be taken, and the value for parameter C in this dataset can be obtained.

For the multistrategy dataset in the paper, parameter for each kind shall be selected through converting the multistrategy data into two prediction datasets. BR method has

Input: training sample set $X = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ and test sample set $X' = \{x_1', x_2', \ldots, x_m'\}$.
Output: effect class i for each test sample x_i'.
Step 1: calculate the effect number.
Step 2: for each test sample $x_i' \in X'$, the following treatment shall be conducted:
(1) For each kind class $j \in Y$ ($Y = \{y_1, y_2, \ldots, y_k\}$), calculate the distance between x_i' and per sample in different kinds, and obtain the candidate distance.
(2) For the obtained candidate distance sequence, calculate the corresponding soft distance for kind class j according to equation (3).
(3) It can be known from equations (6) and (7) that the value of x_i' obtained in equation (1) to soft distance for the sample in different kinds is equal to that for its corresponding lower approximation membership degree. Thus, the lower approximation membership degree of sample x_i' to each kind was obtained.
(4) Corresponding kind strategy class t at the time of the maximum of membership degree shall be selected and returned, and the effect for sample x_i' can be obtained.
Step 3: repeat Step 2 until a kind strategy is obtained for each test sample.

Algorithm 1

different parameter values for different kinds, which can be seen from equation (9). Algorithm transformed by SFRC shall be subject to weighted average of per parameter which is as the value for its penalty factor C. weight is the value for the proportion of strategy quantity to all strategies in each kind, which can be obtained from equation (10).

The equation to calculate parameter C is shown as follows:

$$C_i = \frac{\mathrm{SD}(x, Y) - \mathrm{HD}(x, Y)}{m}, \qquad C = \sum_{i=1}^{L} w_i \times C_i, \tag{15}$$

where L is the total amount of strategy and w_i is the weight of kind i. Credibility for the soft fuzzy lower approximation selected in the experiment of the paper is more than or equal to 95%; that is, sample error rate in the soft superball is less than 5%.

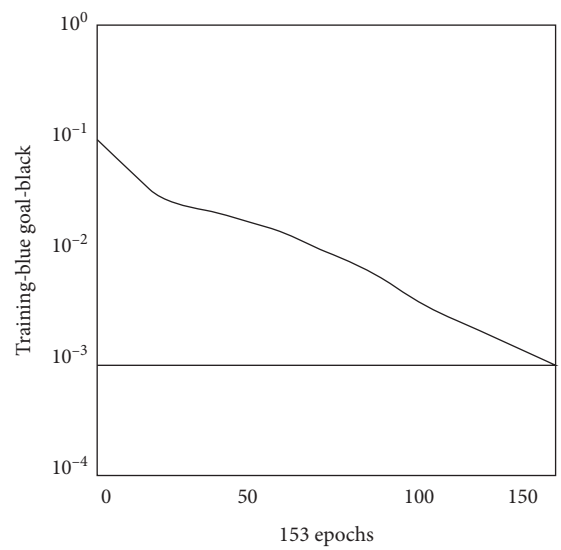

Figure 2: RMSE change curve in the training process.

4. Experimental Analysis

4.1. Convergence Experiment. Since the input level of the rough set is unavoidable, the number of input dimensions will increase exponentially which will inevitably increase the model's large structural complexity and training and learning times. To solve this issue, reduce the impact of subjective factors on the evaluation results, and then adopt the evaluation method on the basis of the layered rough set, we firstly use rough set training simulation in the evaluating indicator and use rough set training simulation in the nonevaluating indicator. Then, we conduct rough set training on their results again, and finally, we evaluate the results of the enterprise. We set the evaluation result as $Y \longrightarrow Z = \{\text{excellent, good, fair, poor}\}$, where Y is the final output of the rough set and Z stands for the performance evaluation for the enterprise grade.

This paper uses training methods and soft fuzzy rough set learning algorithm to calculate, and the evaluating indicator rough set is built with a three-tier model structure. In the structure, the input layer node number is 15, the output layer node number is 1 (i.e., the level of the evaluating position), and the number of hidden layer nodes is 10 (in line with the Kolmogorov theorem). At this time, rough set training error is the smallest, and the training time is the shortest (see Figure 2), where goal is 0.001 and performance is 0.000895863, and the non-evaluating index of the rough set model structure is composed of four nonevaluating indicators as the input and output. The fuzzy layer has 16 nodes, and the number of fuzzy rules is 256. The resulting rough set model structure includes two inputs (level results and evaluating position of nonevaluating rating results) and an output (enterprise performance evaluation results). The fuzzy layer contains eight node number, and the number of fuzzy rules is 16 (see Figure 3). Figure 3 also shows that the mean square error is a relatively smooth curve of the training data, and model training is better.

After the final rough set training is completed, the test sample is put into the well-trained rough set for performance evaluation. Test results' expected output in Figure 4 shows the actual output of the model. From Figure 4, the rough set

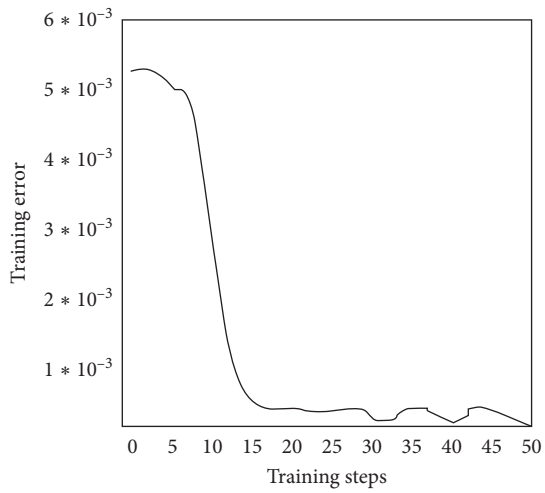

Figure 3: Mean square error of the training data curve.

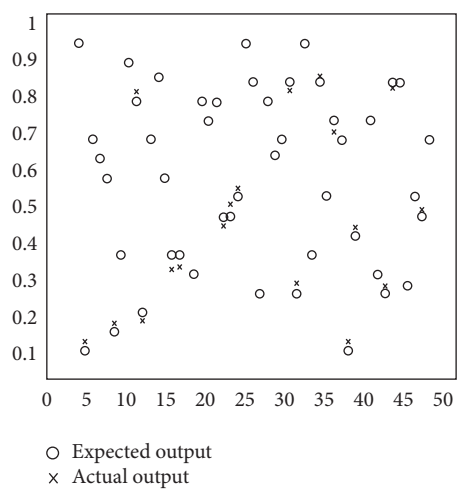

Figure 4: Time output and expected output of the model.

model can be established to facilitate business performance evaluation. The model has a small error between the predicted output and the expected output, with a matching degree of 90%. It thus has higher rating accuracy.

4.2. Comparison for Prediction Effect. The coordinated development research object adopted in [9] shall be selected to analyze the experiment, and contrast algorithm shall be subject to SVM algorithm. SVM is one kind of commonly used prediction model. Coordinated development strategy for multistrategy enterprise is predicted by adopting SVM, and the prediction model for soft fuzzy rough set is formulated. The prediction result for multistrategy predictors is shown in Table 1.

It can be seen from Table 1 that, under the BR method, both SVM algorithm and multistrategy prediction model for the soft fuzzy rough set in the paper can realize effective prediction for the coordinated development strategy of the enterprise, but all indexes in obtained predicted results by utilizing the SVM predictor are worse than the method proposed in this paper, which represents the effectiveness of the proposed algorithm.

It can be seen from Table 2 that the prediction result obtained at the time of adopting boundary to get the expected value is superior to that of giving one fixed threshold.

Table 1: Prediction result for the multistrategy predictor.

Index	Algorithm	
	BR	
	Algorithm in this paper	SVM
Exact match	0.6280	0.6060
Hamming loss	0.0537	0.1006
Accuracy	0.7957	0.7173
Precision	0.9229	0.7756
Recall	0.8154	0.7563
F-measure	0.8475	0.7605

Table 2: Influence result of threshold.

Index	Algorithm					
	Algorithm in this paper					
	90%	92%	94%	96%	98%	Mean
Exact match	0.2990	0.3510	0.3870	0.3870	0.3090	0.6000
Hamming loss	0.5128	0.4373	0.3588	0.2760	0.1988	0.1003
Accuracy	0.4630	0.5141	0.5577	0.5842	0.5606	0.7143
Precision	0.4811	0.5489	0.6234	0.7047	0.7702	0.7806
Recall	0.9694	0.9392	0.8924	0.8174	0.6827	0.7507
F-measure	0.5589	0.6033	0.6425	0.6704	0.6574	0.7583

Seen from the effective prediction value for the coordinated development strategy for the enterprise, the prediction result for nonfixed threshold is obviously lower than the obtained prediction result at the time of adopting boundary to get the expected value, which shows that the prediction performance of algorithm in this paper is more excellent and represents the advantage of the algorithm prediction performance at the time of adopting boundary to get the expected value.

5. Conclusion

In order to cope with the inherent ambiguity and complexity of actual decision-making problems, fuzzy set theory and rough set theory, as two important granular computing methods, can effectively solve problems accompanied by uncertain information. We propose one kind of research method for the coordinated development strategy on the basis of a soft fuzzy rough set. The coordinated development strategy model that is subject to the soft fuzzy rough set for the enterprise is constructed in view of concepts for ecological environment protection. The effect for the enterprise's coordinated development strategy is predicted to get a kind strategy prediction set for each coordinated development strategy. Effectiveness for algorithm is verified in the experimental result. Since the decision-making method using the soft fuzzy rough set combines the advantages of soft fuzzy and rough set, it can deal with fuzzy uncertain and incomplete information well, and it has been widely used in intelligent decision-making. Next research can combine other uncertain mathematical models such as dual-domain rough sets, multigranularity rough sets, and hesitant fuzzy sets, while finding practical applications for scene cases. Algorithm performance shall be further analyzed, and further optimization shall be considered, and then collect the decision rules aimed to further improve the accuracy of enterprise's coordinated development strategy decision-making.

Data Availability

All the data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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