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Research Article

# Partner Selection Optimization Model of Agricultural Enterprises in Supply Chain

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**Abstract:** With more and more importance of correctly selecting partners in supply chain of agricultural enterprises, a large number of partner evaluation techniques are widely used in the field of agricultural science research. This study established a partner selection model to optimize the issue of agricultural supply chain partner selection. Firstly, it constructed a comprehensive evaluation index system after analyzing the real characteristics of agricultural supply chain. Secondly, a heuristic method for attributes reduction based on rough set theory and principal component analysis was proposed which can reduce multiple attributes into some principal components, yet retaining effective evaluation information. Finally, it used improved BP neural network which has self-learning function to select partners. The empirical analysis on an agricultural enterprise shows that this model is effective and feasible for practical partner selection.

**Keywords:** Agricultural supply chain, BP neural network, partner selection, principal component analysis, rough set

## INTRODUCTION

Supply chain of agricultural products contains the whole process from the production, processing, transportation to storage, sales, consumption, etc. Any imperfect session in this process is likely to lead to food safety issues. Building a good partnership is the key problem to supply chain construction and management. Partnership in the supply chain of agricultural products can be defined as: in order to achieve maximum customer value with the lowest cost, a series of interdependent agricultural production and operation enterprises manage the flow and services of agricultural products in the supply chain through close cooperation (Fang, 2009; Omar and Villalobos, 2009). Therefore the relationship among these enterprises is no longer a purely competition relationship. In order to realize the common goal for the best overall efficiency of the supply chain of agricultural products, two or more independent members form a close partnership. They share information, risks and profits over a certain period of time. In this case, how to assess and select partners correctly has become a critical issue for the development of agricultural enterprises.

On the whole, partner selection evaluation method is mainly divided into two kinds of qualitative and quantitative. The former includes bidding, negotiation and intuitive judgment method. The latter includes purchase cost comparison, analytic hierarchy process, ABC cost method, linear weighting method, data envelopment analysis, fuzzy comprehensive analysis and artificial neural network algorithm (Zheng and Lai, 2008; Cao *et al*., 2008; Jabir and Kumar, 2011). Compared with the traditional methods, partner selection in supply chain not only concern about cooperation cost, also consider product quality, flexibility, innovation ability and other factors, so it is more complicated and difficult (Huang and Keskar, 2007). Some scholars in related fields have raised new techniques in terms to solve the uncertainty and productivity issues regarding partner selection (Sun *et al*., 2007; Vincent *et al*., 2009; Ling *et al*., 2010). For instance, Sun looked into the pork production to sales process and then proposed an evaluation index system to choose the suitable pig farm for core enterprise of the pork supply chain. However, the current problem is that people easily overlook the quality safety control, environmentally friendly practices and cooperation synergies which are exactly what matter to partner selection in the supply chain of agricultural products. In weight identification and evaluation value calculation, because of the objective existence of fuzziness is not considered enough, the methods in model is often a lack of adaptability and scientific.

This study focuses on partner selection in supply chain of agricultural products to solve the above-mentioned problem. Firstly, based on comprehensive

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consideration the factors including situation and development prospects of the partners, a comprehensive index system covered most aspects of the partners is proposed. Because of higher dimension and strong correlation of the index system, attribute reduction method PCA-RS merged by Principal Component Analysis (PCA) and Rough Set (RS) is used. This method integrated the advantages of RS for knowledge reduction and PCA for feature extraction and data dimensionality reduction. Finally, based on PCA-RS method, BP neural network model for agricultural products partner selection is constructed, which plays an important role in optimizing agricultural products partner selection.

## LITERATURE REVIEW

**Principal component analysis and rough set:** Principal Component Analysis (PCA) is a mathematical method that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (Howley *et al*., 2006; Babaoğlu *et al*., 2009; Yang *et al*., 2009). The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed.

Rough Set theory (RS) was proposed by Pawlak (1982) firstly. It is a mathematical tool to study the uncertainty and imprecise knowledge. Now RS is commonly used in data preprocessing of data mining (Zhang *et al*., 2010; Zhang and Zhao, 2010). The basic idea is that the decision table E is described by four-tuple. E is defined as $< U,\ R \cup \mathrm{D},\ \mathrm{V},\ \mathrm{f} >$, where U is domain, R is the condition attribute set of U, D is the decision attribute set of D. V is defined as $U_{a\epsilon R\cup D}V_a$ where Va is range of parameter a. $f: U \times (R \cup D) \rightarrow V$ is the information function which means that while $\forall \mathrm{x}\epsilon\mathrm{U}$ and $\mathrm{a}\epsilon\mathrm{R} \cup \mathrm{D}$, then $f(\mathrm{x}, \mathrm{a}) \rightarrow V_a$.

**Back propagation neural network:** Back Propagation (BP) neural network is a multilayered feed-forward neural network based on error back propagation (Xiao and He, 2011). It is a common method of training artificial neural networks so as to minimize the objective function. It's widely used multi-stage dynamic system optimization method. The model is a large-scale parallel processing nonlinear analog system of self-learning, self-organizing, adaptive, whose topology includes input layer, hidden layer and output layer. BP algorithm by iteratively processing a set of training samples, each sample network is compared with actually class label. For each training sample, constantly revised mean square error between the network prediction and the actual class through modifying the right, so that the error function along the negative gradient direction decline and ultimately achieve convergence, the learning process stops.

## PARTNER SELECTION MODEL BASED ON PCA-RS-BP

Firstly, the PCA-RS heuristic algorithm is used for dimensionality reduction and high-dimensional index attribute reduction in the premise of retention evaluation information. Then, principal components obtained by reduction are used as the input of the neural network. Finally, partner selection is achieved by BP neural network self-learning function. The model is shown in Fig. 1.

**Construction of partner selection index system:** Based on agricultural supply chain pattern, related enterprises are generally considered to be demand and supply relationship. It will only be mutually beneficial to both parties if the conjoint enterprises operate spontaneously and simultaneously. Therefore, based on previous studies and combined with the specific factors affecting the choice of partners in the current supply chain management environment, in accordance with a comprehensive, concise, scientific and rational principle, 34 indicators are used for agricultural products supply chain partners selection. The index system is shown in Table 1.

Some indicators are explained as follows. Geographic environment and facilities mean production environment of suppliers including supporting facilities, facility layout and site selection. Rate of timely supply refers to timely delivery of products accounted for the proportion of the number of total product order. Compatibility of enterprise culture refers to the supply chain between enterprises of different cultures with a certain inclusive. Integrative management includes production file management such as monitoring of disinfection, additives, etc., quality certification level of product, information resource management and quality safety credit guarantee. Productivity refers to the ability of enterprises to adopt standardized according to the quality and quantity, time production of agricultural products.

**A heuristic algorithm combining RS with PCA:** Because a lot of factors that affect partner selection. For example, depending on the form of cooperation between enterprises in the supply chain of agricultural

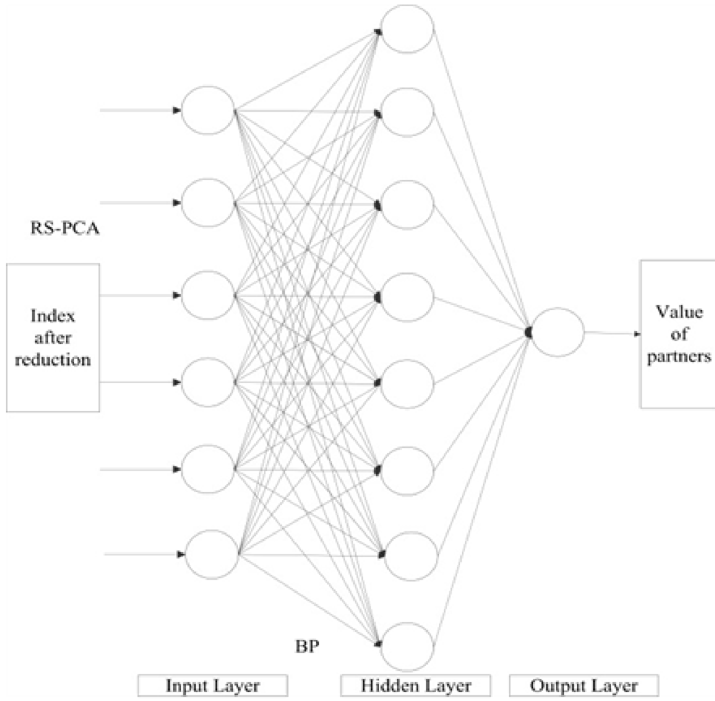


Fig. 1: Partner selection model of agricultural supply chain based on PCA-RS-BP

Table 1: Partner selection index system in agricultural supply chain

| Number | Indicator |
|---|---|
| 1 | Company type |
| 2 | Staff size |
| 3 | Rationality of management team |
| 4 | Creditability |
| 5 | Rationality of capital structure |
| 6 | Profitability |
| 7 | Cash turnover |
| 8 | Financial soundness |
| 9 | Staff self-learning ability |
| 10 | Productivity |
| 11 | Rate of timely supply |
| 12 | After-sale service |
| 13 | Market share |
| 14 | Logistics cost |
| 15 | Equitable price |
| 16 | Supply acceptability |
| 17 | Supply flexibility |
| 18 | Technical cooperation |
| 19 | Compatibility of strategic idea and management concept |
| 20 | Compatibility of management control |
| 21 | Compatibility of enterprise culture |
| 22 | Information resources sharing |
| 23 | Environmental quality system |
| 24 | Cleaner production level |
| 25 | Environmental efficiency |
| 26 | Equipment running ability |
| 27 | Input management |
| 28 | General management |
| 29 | Use and maintenance level of information system |
| 30 | Geographic environment and facilities |
| 31 | Lifecycle of agricultural products |
| 32 | Jointing cost of enterprise |
| 33 | Material cost |
| 34 | Quality control |

products, the partner selection mechanism is different. Or different approaches angle proposed by different scholars for partner selection apply to a particular scene. Therefore, multi-aspect and synthesized index system needs to be constructed. Attributes could be individually independent or correlated. In this case, PCA is used to extract principal components which are Independent for each other. Then the data are divided into equivalence classes according to the principal components. The contribution rate of principal components is obtained at the same time. It illustrates the importance of the principal component of the decision attribute and therefore can be used as a heuristic rule of attribute selection. Then, indistinguishable relationship is used for principal component reduction to obtain relative reduction of attributes set and test these relative attribute set, eventually there are no redundant set of attributes.

**Definition 1:** Heuristic function H $(a_i)$, in this function, $i = 1, \ldots, k$. $p_1, p_2, \ldots, p_k$ are the principal components of decision system E = $<U, R \cup D, V, f>$, where $p_i$ is the $i$-th principal component, $c_i$ is the contribution rate of $p_i$. When the contribution rate of accumulative total of variance is $\eta_k \geq 85\%$, then $V$ equals to $p_1\ c_1 + \ldots + p_k\ c_k$. The equation $H(a_i) = c_i$ is used as heuristic information for searching the smallest reduction of knowledge, which can reduce search space. Meanwhile, PCA condenses the original decision-making table of agricultural products data whose elements are sample attributes to a new one whose elements are P.

**Theorem 1:** Let $U$ is the universe, $R = P = \{p_1, p_2, \ldots, p_k\}$ is one conditional attribute set of $U$, $a$ is one attribute of $R$, $D$ is the decision-making attribute set. The $U$ consistent with $D$ on $R$, then the necessary and sufficient condition is $H(D|R) = H(D|R\text{- }\{a\})$ when $a$ is the redundancy of $R$ related to $D$.

**Theorem 2:** If ind (R- $\{C_i\}$) ≠ ind (R), then (R- $\{C_i'\}$) is not equal ind ($R$) with the increase of elements in set $C_i$ named $C_i'$.

**Input:** $E = <U, R\cup D, V, f>$, where U is domain, R is the condition attribute set of U, D is the decision attribute set of D, (R = P = $\{p_1, p_2, \ldots, p_k\}$).

**Output:** A reduction attributes set of $E$.

**Step 1:** Calculate the contribution rate of principal components $C_i$.
According to V = $p_1$ $c_1$+…+ $p_k$ $c_k$., the associated $H(a_i)$ is obtained as the heuristic function of rough sets.
**Step 2:** Sort by $H(a_i)$ descending, all instances are divided to equivalence classes by principal component $p$.
**Step 3:** Calculate indiscernibility relation ind ($R$) of $R$.
**Step 4:** For ($j = 1 \rightarrow k$)
It selects the largest contribution rate of principal components $p_j$ according to $H(a_i)$. Then it calculates ind (R- $\{p_j\}$).
If (ind (R- $\{p_j\}$) ≠ ind (R)) then algorithm does not test attributes *pj*
Else jump to Step 5
**Step 5:** If (ind (R- $\{p_i - p_j\}$) ≠ ind (R)) then as a single attribute $p_i$, $p_j$ is redundant. Else, repeat the Step 4 and the Step 5 until all combinations of ($p_i$, $p_j$) calculation is completed
**Step 6:** **Test stage:** One relative reduction set of $R$ is $R = \{p_1, p_2, \ldots, p_I\}$ after five steps mentioned above.
For ($n = 1$; $n <= N$; $n$++)
If ($H(D|R) = H(D|R\text{- }\{p_n\})$) then
$p_n$ is a redundancy attribute
Else
$R = \{p_1, p_2, \ldots, p_I\}$ is a reduction set of $R$
**Step 7:** Get a reduction of R where R = R- $\{p_n\}$
End

**Improved BP neural network algorithm:** Traditional BP neural network in the correction of the weights, the convergence rate is relatively slow, oscillation phenomenon occurs often in the training process and is easy to fall into local minimum point. Therefore, by increasing the momentum term and adaptive adjustment of the learning rate improved BP neural network algorithm to accelerate the convergence process, in order to improve the learning speed. In this study, the attributes get from heuristic algorithm is as the input variables of the neural network, the qualitative scoring and quantitative calculations by industry experts and researchers come to the partners index score and then multiplied by the principal component analysis of the resulting index weights as output variable.

The parameters setting of hidden layer and output layer are as follows. Given a hidden layer or the output layer unit $j$, $I_j$ is the net input to unit $j$ where, $I_i = \sum_i w_{ij} o_i + \theta_j$. In the above formula, $w_{ij}$ is right weight connecting the upper layer unit $i$ to unit $j$, using Sigmoid excitation function acting on the net input $I_j$, then $O_j$ of unit $j$ is obtained. Calculate the error of each output layer unit $j$ and the error of each hidden layer $k$. Continually update the connection weights and thresholds; the change in the value of the weights $\Delta W(t)$ equals to $-lr\frac{\partial E_p}{\partial W} + v\Delta W(t-1)$ is correction value of connection weights at $t$-th iteration. $\triangle W(t\text{-}1)$ *is* correction value of connection weights at ($t$-1)-th iteration, $v$ is momentum factor, $lr$ is the learning rate and $E_p$ is the variance between the actual value and the desired output.

**Empirical analysis:**

**Data preparation and preprocessing:** Ninety partners of the past five years to an agricultural enterprise are selected as samples. The samples which include transaction data and other information are used to partners grading. Sample data are preprocessed in order to discretize the continuous attribute value firstly. For example, scale of staff is more than 1000 people can stand by 100, more than 500 and less than 1000 can stand by 80, more than 100 and less than 500 can stand by 60, more than 50 and less than 100 can stand by 40 and less than 50 people an stand by 20. These decision-making factors such as reasonableness of the capital structure and production capacity which are more abstract and vague can use relative scoring method to quantify. It means that the strongest company in the industry is as a benchmark and other partners to be evaluated and comparative evaluation. For instance, an enterprise A whose production capacity is best set 100 points, the other candidate partners determine their appropriate level score by compared with the enterprise. The grade determination is scored by expert and business people. On the basis of full consultation with experts, grading standard of partners is set in Table 2.

**Heuristic algorithm for attribute reduction:**

- PCA is performed after preprocessing and seven principal components with above 85% contribution rate are obtained, which can be see n in Table 4. Table 3 shows the corresponding relation between principal components and original index.

Table 2: Grading standard of partners

| Grade/index | Excellent | Good | Moderate | Qualified | Poor |
|---|---|---|---|---|---|
| Second-class 1 | 100-90 | 89-80 | 79-70 | 69-60 | 59-0 |
| Second-class 2 | 100-90 | 89-80 | 79-70 | 69-60 | 59-0 |
| Second-class n | 100-90 | 89-80 | 79-70 | 69-60 | 59-0 |

Table 3: Corresponding relation between principal components and original index

| Number | Principal component variables | Key features |
|---|---|---|
| 1 | Business to business cooperation ($P_1$) | Compatibility of strategic plans and operation principles, management control, enterprise culture and information and technology |
| 2 | Supply ability ($P_2$) | Lifecycle of agricultural products and timeliness and acceptability of supplies |
| 3 | Quality safety control ($P_3$) | Geographical environment, facilities, hygiene and epidemic prevention and integrated management |
| 4 | Competitive power ($P_4$) | Agricultural products' overall quality and cost, after-sale service, product marketing, equitable price and logistics cost |
| 5 | Environmental protection ($P_5$) | Environmental quality system, cleaner production and present eco-efficiency |
| 6 | Sustainable development ($P_6$) | Creditability, capital structure, profitability, cash turnover, financial soundness and information system maintenance |
| 7 | Corporation information ($P_7$) | Form of business enterprises, staff size, management team, staff self-learning ability, production capacity |

Table 4: Contribution of principal component

| | Eigen value | Contribution rate (%) | Total contribution rate (%) |
|---|---|---|---|
| The first component | 4.2468 | 30.2647 | 30.2647 |
| The second component | 4.0113 | 25.2124 | 55.4771 |
| The third component | 3.3554 | 13.2126 | 68.6897 |
| The fourth component | 2.7368 | 11.3468 | 80.0365 |
| The fifth component | 1.1204 | 3.7831 | 83.8196 |
| The sixth component | 0.6122 | 0.7574 | 84.5770 |
| The seventh component | 0.5318 | 0.4783 | 85.0533 |

- Heuristic algorithm is used to reduce attribute of sample T after principal component dimensionality reduction, then generate a set of attributes R which is $\{P_1, P_2, P_3, P_4, P_5, P_6, P_7\}$.

The first step, doing equivalence partitioning on sample in accordance with the principal component.

The second step is to obtain indiscernibility relation of $R$ which is ind ($R$) U/ind ($R$).

The third step, calculate indiscernibility relation of (R- $\{P_1\}$), (R- $\{P_2\}$), (R- $\{P_3\}$), (R- $\{P_4\}$), (R- $\{P_5\}$), (R- $\{P_6\}$) and (R- $\{P_7\}$) separately, then obtain ind (R) which equals to ind (R- $\{P_5, P_6, P_7\}$). Therefore, redundant attributes are existing in attribute sets.

The fourth step, calculate indistinguishability relation of complement of all combinations between attributes. The result is ind (R) does not equal ind (R- $\{P_5, P_6\}$). Therefore, all attributes of R are independent of each other, so the relative reduction of $R$ expressed as $Q$ that $Q$ equals to ($P_1$, P2, P3, P4, P7).

The fifth step, calculate condition entropy H (D| Q), while computing H (D | $B_1$- $\{P_1\}$), H (D | $B_1$- $\{P_2\}$), H (D | $B_1$- $\{P_3\}$), H (D | $B_1$- $\{P_4\}$), H (D | $B_1$- $\{P_7\}$)), the above conditional entropy are not equal to H (D | Q) which shows that there is no redundancy properties in property set Q.

The sixth step, the reduction Q of R is obtained. Q equals to (Business to Business Cooperation, Supply Ability, Quality Safety Control, Competitive Power, Corporation Information).

**Establishment and training of BP neural network model:** 2/3 of the sample data are randomly selected as training samples and the rest treated as test samples. They are used to build and train BP neural network model. The nodes number of input layer is the number of principal component. The nodes number of hidden layer obtains by "trial and error" method, in accordance with the experience, six nodes are adopted. In this case, the training will stop if the number of training times doesn't converge within a specified training number. Then, re-perform as more nodes are added in hidden layer. Finally, error equals to $10^{-4}$ while nodes of input layer equals to 6 = r and nodes of hidden layer equals to 8. The initial learning rate lr set to 0.7, the number of iterations $N$ set to 10000 and the momentum factor $v$ set to 0.6. MATLAB neural network toolbox is used and traingda learning method is adapted to train samples. After 874 times learning, the error value drops below 0.0001, the end of the calculation, network convergence is reached.

## RESULT ANALYSIS

After training completed, the rest 1/3 sample are used as test sample. Through simulation of the established BP neural network model, 30 outputs are obtained. Using relative error indicators evaluation, partial results are shown in Fig. 2.

According to the model of learning results, parts of rules are extracted. As shown in Table 5, rule $D$ represent partner level in the supply chain of agricultural enterprise. The score of $D$ is from 1 to 5, the larger the number, the higher the level and the more intense willingness to cooperate.

The running time and accuracy are compared by PCA-RS-BP and BP models based on different data sets in Fig. 3 and 4.

Seen from the Table 5, with the expansion of the scale of the sample dataset, the time efficiency of BP is significantly lower than the PCA-RS-BP. Although the accuracy rate of BP is slightly higher than the PCA-RS-BP, but as the data set increases, the accuracy of the

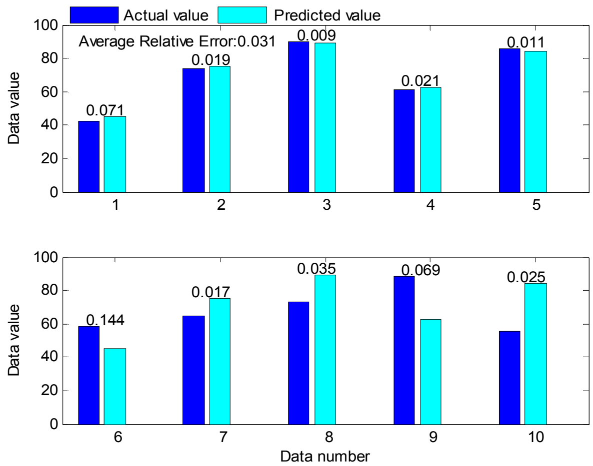


Fig. 2: Error analysis

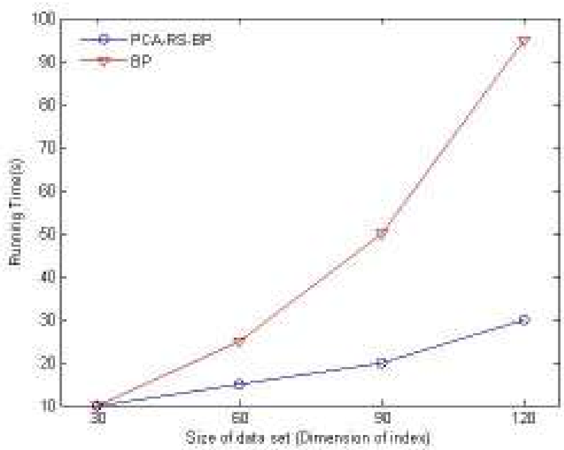


Fig. 3: Comparison between PCA-RS-BP and BP (running time)

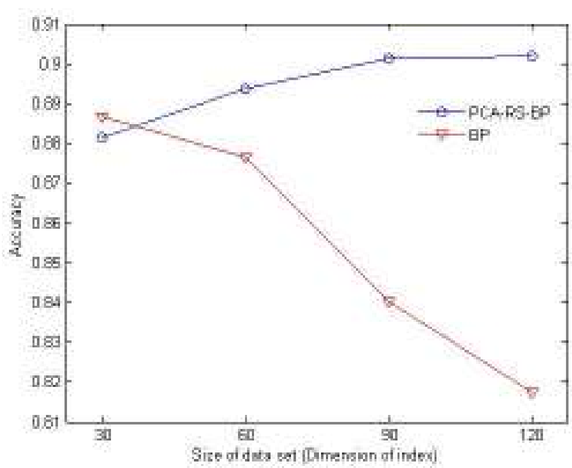


Fig. 4: Comparison between PCA-RS-BP and BP (accuracy)

proposed method is superior to BP and has good generalization. Combined high dimensional attributes of partners' indicator in actual agricultural supply chain, the proposed method can play a better role attribute reduction, more in line with the actual application scenarios. Therefore, the new PCA-RS-BP model is more effective.

Table 5: Partner selection rules list

| ID | Rule |
|---|---|
| 1 | $P_1 = 5 \wedge P_2 = 5 \wedge P_3 = 5 \Rightarrow D = 5$ |
| 2 | $P_1 = 4 \wedge P_3 = 3 \wedge P_4 = 5 \Rightarrow D = 4$ |
| 3 | $P_1 = 2 \wedge P_3 = 3 \wedge P_7 = 3 \Rightarrow D = 3$ |
| 4 | $P_2 = 5 \wedge P_3 = 4 \wedge P_7 = 5 \Rightarrow D = 1$ OR $D = 5$ |
| 5 | $P_1 = 5 \wedge P_2 = 3 \wedge P_3 = 3 \wedge P_4 = 5 \Rightarrow D = 5$ |
| 6 | $P_1 = 4 \wedge P_2 = 3 \wedge P_3 = 5 \wedge P_4 = 4 \Rightarrow D = 4$ |
| 7 | $P_2 = 5 \wedge P_3 = 4 \wedge P_4 = 4 \Rightarrow D = 4$ OR $D = 1$ |
| 8 | $P_1 = 5 \wedge P_2 = 5 \wedge P_3 = 5 \wedge P_4 = 2 \wedge P_7 = 2 \Rightarrow D = 5$ |
| 9 | $P_1 = 4 \wedge P_2 = 4 \wedge P_3 = 5 \wedge P_4 = 3 \wedge P_7 = 3 \Rightarrow D = 4$ |
| 10 | $P_1 = 2 \wedge P_2 = 5 \wedge P_3 = 2 \wedge P_4 = 3 \wedge P_7 = 2 \Rightarrow D = 2$ |
| 11 | $P_1 = 2 \wedge P_2 = 5 \wedge P_3 = 2 \wedge P_4 = 4 \wedge P_7 = 5 \Rightarrow D = 4$ OR $D = 2$ |
| 12 | $P_1 = 1 \wedge P_2 = 5 \wedge P_3 = 5 \wedge P_4 = 5 \wedge P_7 = 5 \Rightarrow D = 4$ OR $D = 1$ |

Table 6: Results between FCE and PCA-RS-BP

| Company | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| FCE | 0.83 | 0.75 | 0.79 | 0.62 | 0.78 |
| Ordered by FCE | 1 | 4 | 2 | 5 | 3 |
| PCA-RS-BP | 4.23 | 1.13 | 3.05 | 0.98 | 2.98 |
| Ordered by PCA-RS-BP | 1 | 4 | 2 | 5 | 3 |

It used Fuzzy Comprehensive Evaluation (FCE) to test the rationality of partner selection and optimization results:

$$B = w \circ R = (0.30 \quad 0.25 \quad 0.13 \quad 0.11 \quad 0.48) \circ \begin{pmatrix} 0.47 & 0.29 & 0.12 & 0.07 & 0.03 \\ 0.48 & 0.32 & 0.12 & 0.04 & 0.05 \\ 0.42 & 0.24 & 0.14 & 0.07 & 0.03 \\ 0.40 & 0.36 & 0.15 & 0.01 & 0.04 \\ 0.41 & 0.29 & 0.21 & 0.05 & 0.05 \end{pmatrix}$$

$R_{ij}$ is the membership index of grade to indexes, W is the contribution rate of component. Paper selected five partners to compare the results between FCE and PCA-RS-BP.

Results demonstrate the validity and rationality of this method (Table 6).

## CONCLUSION

This study established a partner selection model for agricultural enterprises. Based on the study of PCA feature extraction and RS attribute reduction, combined with the characteristics of the agricultural data, an attribute reduction method based on RS and PCA is proposed. This method can solve the high dimensional attributes correlation and subjectivity in index determination. Through the true application in an agricultural enterprise, this model is proved to be feasibility. It not only reduce the randomness of the indicators selection and model training time, but also to ensure the accuracy and validity of the results of the evaluation and mining scientific rules of partner selection. Besides, the generalization ability of this model has to a great extent demonstrated its application value in related fields.

## ACKNOWLEDGMENT

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