A Novel Back Propagation Neural Network Optimized by Rough Set and Particle Swarm Algorithm for Remanufacturing Service Provider Classification and Selection

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Abstract. Aiming at the problem that the high classification feature dimensionality of the back propagation neural network (BPNN) leads to slow convergence speed and the initial weight and threshold sensitivity of the BPNN lead to the problem of easy convergence to the local optimum. A novel BPNN optimized by rough set and particle swarm algorithm (RS-PSO-BPNN) for remanufacturing service provider classification and selection is proposed. First, the attribute reduction method of rough set theory is used to preprocess the classification features of remanufacturing service providers, redundant attributes are deleted from the decision table, and the input feature dimension is reduced; then the PSO algorithm is used to optimize the network Initial weight and threshold. Finally, the proposed method is used for the selection and optimization of remanufacturing service providers. The results show that the proposed RS-PSO-BPNN has higher classification accuracy and efficiency for the problem, which provides scientific decision supports for remanufacturing service provider selection.

1. Introduction

Remanufacturing is one of the effective strategies to improve the product life cycle and achieve sustainable production [1, 2]. After the remanufacturing was proposed, it has attracted the attention of many countries all over the world and has developed rapidly [3]. The practice gives products of equal even better quality to conventional manufacturing for reduction up to 60% energy, 70% materials, 50% cost, 80% air pollution[4]. The remanufacturing industry represented by the United States, Japan and Europe has a history of more than 50 years and has formed a very mature remanufacturing industrial chain. China’s ‘14th Five-Year’ Circular Economy Development Plan also proposes to promote the high-quality development of the remanufacturing industry.

Different from traditional manufacturing, the remanufacturing process generally includes waste product recycling, cleaning, testing, disassembly, remanufacturing design, remanufacturing, re-sales and
other activities, and each step is highly professional. Remanufacturers publish their remanufacturing capabilities, such as cleaning, disassembly, etc., to the remanufacturing service platform in the form of services. And remanufacturing demanders find suitable remanufacturers on the remanufacturing service platform according to their needs [5]. During the remanufacturing process, high-quality remanufacturing service providers are an important prerequisite for achieving green, efficient, and low-cost remanufacturing. Therefore, how to choose remanufacturing service providers scientifically and effectively is an important issue to remanufacturing demanders.

At present, there are more researches on traditional manufacturing supplier selection. The researches of supplier selection are mainly concentrated on the selection evaluation index system and evaluation method. Related researches on supplier evaluation index system include the 23 indexes of supplier selection [6], the three main principles [7] and so on. Supplier evaluation methods are mainly AHP [8], fuzzy c-means (FCM) [9], BPNN [10] etc. Yin analyzed the relationship of remanufacturing service and Quality of Service (QoS), as well as the characteristics of the existing common evaluation index of manufacturing service [11]. The current research mainly focuses on the selection of traditional manufacturing suppliers, and there are few researches on remanufacturing service providers.

Due to the big difference between remanufacturing and traditional manufacturing, the evaluation indicators and methods are also different. There are few studies on the selection of remanufacturing service providers. Therefore, this paper proposes a remanufacturing service provider classification and selection method based on RS-PSO-BPNN. Rough set (RS) is used to discover the core evaluation indexes of the remanufacturing service providers. The back propagation neural network (BPNN) is used to construct a remanufacturing service provider classification model so as to reduce the complexity in the traditional supplier selection procedures. Because the parameters of BPNN have a significant influence on results, and particle swarm optimization (PSO) is capable of quickly finding optimal solutions, PSO and BPNN have been integrated so that the convergence rate is improved and precision is relatively enhanced.

2. The remanufacturing service provider selection model based on RS-PSO-BPNN

The algorithm flow based on RS-PSO-BPNN for remanufacturing service provider selection is shown in Figure 1.

![Figure 1. The algorithm flow based on RS-PSO-BPNN for remanufacturing service provider selection model](image-url)
In this model, firstly, the rough set method is used to determine the evaluation indexes of the remanufacturing service provider, and the BPNN network structure is determined according to the indexes. Then, the initial weights and thresholds of BPNN are determined through the PSO algorithm. Finally, the neural network will be trained with sample data. When the training achieve the precision, we can use this BPNN to classify the remanufacturing service provider.

2.1. Construction of Evaluation Index System
Remanufacturing service provider evaluation index system is an important part of remanufacturing service provider selection. Whether index selection is appropriate, affects the remanufacturing service provider selection. Combined with remanufacturing industry enterprise and related research results, a two-level remanufacturing service provider evaluation index system is established, which includes 5 first-level indexes and 15 second-level indexes. The first level indexes are remanufacturing quality, remanufacturing cost, company strength, greenness and service level. The second level indexes are remanufacturing grade, remanufacturing qualification ratio, remanufacturing price level, remanufacturing cost, asset capacity, technical level, enterprise credit, overall management level, qualification certification, Energy consumption, carbon emission, material utilization, timeliness of Service, service professional, service attitude, shown in Figure 2.

2.2. Reduction of evaluation indicators
Rough set is an effective method of data set reduction [12]. Rough set theory is proposed by Pawlak in 1982 [13]. Reducing the evaluation indicators of remanufacturing service providers through rough sets mainly includes the following steps [14].

2.2.1. Knowledge Representation System. A knowledge representation system or information system S can be represented as a four-tuple $S = \{U, R, V, f\}$, and $U = \{x_1, x_2, \ldots, x_n\}$ is a collection of all samples; $R = C \cup D$ is attribute collection, and subset $C$ is condition attribute set reflecting the characteristics of the objects, $D$ is decision attribute set reflecting the class of the object. $V = \bigcup_{r \in R} V_r$ is a collection of property values, $V_r$ represents the range of attribute $r$. $f : U \times R \rightarrow V$ is an information functions that used to determine the attribute values of each object $X$ in $U$, namely for any $x_i \in U$, $r \subseteq R$, there is $f(x_i, r) = V_r$. 

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**Figure 2.** Remanufacturing service provider evaluation indicator system
2.2.2. **Indiscernible Relation.** Namely for any subset of attributes \( B \subseteq \mathbb{R} \), objects \( x_i, x_j \subseteq U \), \( \forall r \subseteq B \), and only if \( f(x_i, r) = f(x_j, r) \), \( x_i \) and \( x_j \) are indistinguishable, abbreviated as \( \text{Ind}(B) \). Indiscernible relationship is also called an equivalence relation.

2.2.3. **Upper and Lower Approximation.** Lower approximation set: Analyzing the set composed of all objects in \( U \) that definitely belong to the set \( X \) according to existed knowledge \( R \),

\[
\mathcal{R}(X) = \{ x \mid (\forall x \in U) \land ([x]_R \subseteq X) \}
\]  

where \([x]_R\) represents equivalence class whose equivalence relation \( R \) contains element \( X \).

Upper approximation set: Analyzing the set composed of all objects in \( U \) that definitely or possibility belong to the set \( X \) according to existed knowledge \( R \),

\[
\tilde{\mathcal{R}}(X) = \{ x \mid (\forall x \in U) \land ([x]_R \cap X \neq \emptyset) \}
\]

where \([x]_R\) represents equivalence class whose equivalence relation \( R \) contains element \( X \).

Given knowledge representation system \( S = \{ U, R, V, f \} \), for each sample subset \( X \subseteq U \) and equivalence relation \( R \), the union of basic sets that contained in \( X \) is \( \mathcal{R}(X) \); the union of basic set that the intersection of the \( X \) is not empty is \( \tilde{\mathcal{R}}(X) \).

2.2.4. **Knowledge Reduction.** Setting \( Q \subseteq P \), if \( Q \) is independent and \( \text{Ind}(Q) = \text{Ind}(R) \), \( Q \) is a reduction of equivalence family, which is denoted by \( \text{Red}(P) \). The set of all relation that cannot be omitted in \( P \) is called the core of equivalence relation family, which is denoted by \( \text{Core}(P) \).

The relationship between knowledge reduction and core: the intersection of \( \text{Red}(P) \) and reduction set is equal to the core of \( P \), namely:

\[
\text{Core}(P) = \cap \text{Red}(P)
\]  

In one aspect, the core is the basic of the calculation of reduction. In another aspect, the core is the most important part of the knowledge base which cannot be deleted when knowledge reduction is conducted.

2.2.5. **Decision Table.** Decision table is a special kind of knowledge representation system. Setting \( S = \{ U, R \} \) as a knowledge representation system, if \( R \) can be divided into condition attribute set \( C \) and decision attribute set \( D \), there is \( C \cup D = R, C \cap D = \emptyset \). Knowledge representation system with conditional attributes and decision attributes can be expressed as a decision table, denoted by \( T = \{ U, R, C, D \} \) or named as \( CD \) decision table. The equivalence class of \( \text{Ind}(C) \) is called condition class and the equivalence class of \( \text{Ind}(D) \) is called decision class.

2.3. **Classification and Selection based on improved BPNN**

PSO is used to optimize BPNN’s initial weight and thresholds. Use the weights and thresholds of BPNN as individuals of PSO, and use BPNN output error as fitness function value. When the iteration reaches the set number of times or the output error reaches the specified accuracy, BPNN gets the optimal weights and thresholds. PSO regards each individual as a particulate flying in a certain speed at the search space in D-dimensional search space. The speed is adjusted by its own experience and the
experience of its flying companion. A particle can be represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, the best position it experienced is denoted as $p_i = (p_{i1}, p_{i2}, \ldots, p_{id})$, also known as $p_{best}$. All particles in the population experienced the best index of the position is expressed by symbol $g$, which is also known as $g_{best}$. The speed of partials is represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. For each generation, section D-dimensional ($1 \leq d \leq D$) changes according to the equation (4, 5) [15].

$$V_i = \left( w v_{id}^{k-1} + c_1 r_{an} \left( p_{id} - x_{id}^{k-1} \right) + c_2 r_{an} \left( p_{gd} - x_{id}^{k-1} \right) \right)$$  \hspace{1cm} (4)$$

$$x_{id}^k = x_{id}^{k-1} + v_{id}^{k-1},$$  \hspace{1cm} (5)

Where $w$ is Inertia weight, $c_1$ and $c_2$ are Constant acceleration, $r_{an}1$ and $r_{an}2$ are random functions in the range 0-1. The speed of particle $V_i$ is limited by a maximum speed. If the current acceleration of speed makes particle faster than the maximum speed of the dimension, the speed for the dimension is limited to the maximum speed $V_{max}$.

3. Case Study

3.1. Sample Data Acquisition

260 remanufacturing suppliers are obtained from a remanufacturing service platform. 200 remanufacturing service providers are randomly selected as sample data; the remaining 60 remanufacturing service providers are used as test data. Part of the data are shown in Table 1.

In this knowledge system, condition attributes $C = \{C_{11}, C_{12}, C_{21}, C_{22}, C_{31}, C_{32}, C_{33}, C_{34}, C_{35}, C_{41}, C_{42}, C_{43}, C_{44}, C_{45}, C_{46}, C_{47}, C_{48}, C_{49}, C_{51}, C_{52}, C_{53}\} = \{ \text{remanufacturing grade, remanufacturing qualification ratio, remanufacturing price level, remanufacturing cost, asset capacity, technical level, enterprise credit, overall management level, qualification certification, Energy consumption, carbon emission, material utilization, timeliness of Service, service professional, service attitude} \}$. Decision attribute $D$ is the category of remanufacturing supplier, where $D = \{\text{Excellent, good, bad}\}$.

| S  | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 | D       |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|--------|
| S1 | 52 | 55 | 55 | 79 | 65 | 60 | 50 | 50 | 50 | 59 | 59 | 60 | 50 | 55 | 50 | Excellent |
| S2 | 88 | 70 | 43 | 36 | 70 | 90 | 80 | 90 | 90 | 85 | 50 | 90 | 60 | 60 | 60 | Excellent |
| S3 | 93 | 80 | 79 | 92 | 85 | 85 | 70 | 95 | 85 | 94 | 93 | 80 | 70 | 95 | 80 | Excellent |
| S4 | 55 | 55 | 56 | 80 | 65 | 55 | 50 | 50 | 50 | 57 | 53 | 60 | 60 | 55 | 55 | good     |
| S5 | 90 | 90 | 87 | 97 | 90 | 85 | 99 | 80 | 80 | 81 | 66 | 80 | 80 | 85 | 85 | Excellent |
| S6 | 59 | 55 | 58 | 82 | 65 | 50 | 55 | 50 | 50 | 57 | 53 | 65 | 60 | 55 | 55 | good     |
| S7 | 87 | 65 | 83 | 50 | 80 | 75 | 80 | 99 | 99 | 87 | 93 | 75 | 80 | 85 | 85 | Excellent |
| S8 | 59 | 55 | 53 | 82 | 65 | 60 | 50 | 50 | 55 | 57 | 63 | 65 | 60 | 50 | 50 | good     |
| S9 | 49 | 40 | 30 | 60 | 60 | 50 | 45 | 45 | 45 | 50 | 57 | 55 | 60 | 30 | 50 | 55 | bad      |

3.2. Data Processing

3.2.1. Data Discretization. The values of decision table should be discrete data when rough set is used to process decision tables. In intelligent information processing, continuous data should be pre-treated and discretized, and converted to rough set theory identified data, from which useful information and knowledge is extracted. The above data is discretized, which is shown in Table 2.
3.2.2. Attribute Reduction. A decision table is constructed through above discrete data and the discernible matrix is calculated. After reduced attributes according to the importance, the remaining 9 condition attributes are $C_1$ (remanufacturing grade), $C_2$ (remanufacturing qualification ratio), $C_3$ (remanufacturing price level), $C_4$ (remanufacturing cost), $C_5$ (asset capacity), $C_7$ (enterprise credit), $C_9$ (qualification certification), $C_{11}$ (carbon emission) and $C_{13}$ (timeliness of Service). Its support degree is 100%.

3.2.3. Rule Extraction. In the decision table, a total of 91 decision rules are obtained and one of the rule is shown as: $C_1(2)$ AND $C_2(2)$ AND $C_3(0)$ AND $C_4(0)$ AND $C_5(2)$ AND $C_7(1)$ AND $C_9(1)$ AND $C_{13}(1)$ => $D(2)$.

The reduction attributes and decision rules obtained through the rough set will be used for determining the structure of BPNN.

3.3. PSO-BPNN Training and Testing

3.3.1. Determine the particle swarm dimension. Due to the individual particle swarm is made up of BPNN’s weights and thresholds. Each weight or threshold is one dimension of the particle swarm, the BPNN structure should be decided first. According to the previous rough set reduction properties, the number of input layer node can be set as 9, the number of output layer node is 1 and hidden layer can be set according to inspired formula [16]:

$$i = \sqrt{n + m + a}$$

Where, $i$ is the number of nodes in the hidden layer; $n$ is the number of nodes in the input layer; $m$ is the number of nodes in the output layer; $a$ is a constant and $1 < a < 10$. Here $a$ is taken as 6. Number of nodes in the hidden layer is calculated as 10. BPNN is identified as 9-10-1. So PSO dimension is $D = n \ast i + i + i \ast m + m = 111$.

3.3.2. Determine the parameters of PSO. Set speed maximum limit $v_{\text{max}} = 0.5$, target accuracy $\epsilon = 10^{-6}$, maximum number of iterations $i_{\text{max}} = 250$, acceleration factor $c_1 = c_2 = 1.5$. Make weight decrease with linear iteration times to ensure convergence, $w_n = w_{\text{max}} - (w_{\text{max}} - w_{\text{min}}) / n \ast \text{iter}$, and $w_{\text{max}} = 0.95$, $w_{\text{min}} = 0.25$. Particle number $N = 30$.

3.3.3. Search for the weight and threshold. Input sample data to search after initialization parameters. Iterations are stopped after 250 iterations which is the maximum number. BPNN’s weights and thresholds are initialized by optimal weights and thresholds which are got by PSO and BPNN is trained by the 91 rules obtained through rough. After 69 iterations, BPNN reaches the given accuracy. Training accuracy curve is shown in figure 5.
After the BPNN training, the output results of the remaining 60 test samples are shown in Figure 6. The circle represents the real value, the cross represents the traditional BPNN test value, and the asterisk represents the PSO-BPNN test value. The classification accuracy of BPNN reaches 85.7%, and the classification accuracy of PSO-BPNN reaches 98.3%. The results show that PSO-BPNN has a higher classification accuracy, and the accuracy is greatly improved. At the same time, it also proves the effectiveness of the RS-PSO-BPNN method for the classification of remanufacturing service providers. Decision makers can choose better remanufacturing service providers based on the results.

4. Conclusion

A remanufacturing service provider classification and selection method based on the rough set, particle swarm and BPNN is proposed in this paper. First of all, the evaluation index system of remanufacturing service suppliers is established according to the remanufacturing service process. Then, the rough set method is used to reduce the index system, and 9 core evaluation indexes are obtained, which reduces the difficulty of subsequent classification selection. Finally, in view of the slow convergence of BPNN training, the initial weight and threshold of BPNN are optimized by PSO, which effectively improves the training speed and classification accuracy of BPNN. The optimized BPNN can be trained in 69 iterations and the classification accuracy of the RS-PSO-BPNN method reaches 98.3%, which can provide effective decision support for the selection of remanufacturing service providers.

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References

[1] NR Khalili, S Duecker, W Ashton, F Chavez. From cleaner production to sustainable development: the role of academia [J]. Journal of Cleaner Production, 2015, 96 (1): 30-43.
[2] WM Cheung, R Marsh, PW Griffin. Towards cleaner production: a roadmap for predicting product end-of-life costs at early design concept [J]. Journal of Cleaner Production, 2015, 87 (1): 431-441.
[3] Cao J, Xia X, Wang L, et al. A Novel Multi-Efficiency Optimization Method for Disassembly Line Balancing Problem [J]. Sustainability, 2019, 11(24):1-16.
[4] Khalili, NR., Duecker, S., Ashton, W.,Chavez, F., 2015. From cleaner production to sustainable development: the role of academia. Journal of Cleaner Production, 96(1):30-43.
[5] Wang Lei, Guo Yuyao, Zhang Zelin, Xia Xuhui. Extensive Concept, State-of-the Art Developing
Trends of Remanufacturing Service [J]. Journal of Mechanical Engineering, 2021, 57(7):138-153.

[6] Dickson. An analysis of vendor selection system and decisions [J]. Journal of Purchasing, 1996, 2: 28-41.

[7] XIA Hui. Selection of Strategic Suppliers Participating in Product Development [J]. Science and Technology Management Research, 2012, 32(22).

[8] Xu Jianzhong, Sun Ying, Sun Xiaoguang. Green supplier selection based on the fuzzy C-means-VIKOR model of genetic search weights [J]. Statistics and Decision, 2021, 37(04): 159-163.

[9] Sun Xiaolin, Jin Chun, Ma Lin, Wang Wenbo. Supplier matching method based on ontology and fuzzy QoS in cloud manufacturing environment [J]. Chinese Management Science, 2018, 26(01): 128-138.

[10] Lv Yunlong. Research on the Evaluation of Equipment Supplier Selection of Company B Based on FA&BP Neural Network [D]. China University of Mining and Technology, 2019.

[11] Yin Lu, Xia Xuhui, Zhou Min, Wang Lei. QoS-based remanufacturing service evaluation method [J]. Machine Design and Manufacturing, 2016(11):265-269.

[12] Liu Zhanfeng, Pan Su. Fuzzy Rough Set Double Reduction Algorithm Based on Particle Swarm Optimization [J]. Journal of Beijing University of Posts and Telecommunications, 2021, 237: 1-7.

[13] Z. Pawlak, Rough sets, International Journal of Computer and Information Sciences [J] 11, 1982, 341–356.

[14] Miao Duoqian, Li Daoguo. Rough Sets Theory Algorithms and Application [M]. Tsinghua university press, 2008(1).

[15] ZHOU Min, WANG Qiong, XING Jie-bing. Study on Logistics Customer Satisfaction Based on Fuzzy-EAHP [J]. LOGISTICS TECHNOLOGY, 2011, 30(4):79-81.

[16] Li Biao, Yuan Guoliang, Zhu Ruqi, Xie Kui. WIFI-assisted IMU indoor joint positioning based on BP neural network [J]. Computer Simulation, 2021, 38(07): 442-446.