Research on Vehicle and Goods Matching Optimization and Recommendation Model of Network Freight Platform

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Abstract. Network freight platforms face the complex task of truck-goods matching, which involves considering user conditions and demands. The matching process evaluates ten indicators, such as vehicle type and reputation, using intuitionistic fuzzy rough sets to represent scores and degrees of satisfaction, dissatisfaction, and hesitation. An optimization model based on prospect theory, with the zero point as a reference, maximizes the comprehensive foreground value. A multi-attribute fuzzy decision model is constructed to optimize overall satisfaction, transforming intuitionistic unclear data into a decision matrix and comparing distances to ideal and negative ideal schemes for ranking. Experimental data from a freight platform shows that the algorithm achieves the highest recommendation accuracy when handling 100 users and 20 items, increasing matching satisfaction by 13.8% over traditional collaborative filtering methods. The algorithm maintains the lowest average absolute error (MAE) value of 0.536, boosting the accuracy rate by 23.4%, and offers effective decision support for improving matching efficiency and recommendation satisfaction on the platform.

Keywords: car-goods matching; intuitive fuzzy rough set; prospect theory; multi-attribute fuzzy decision

1 INTRODUCTION

In the information age, leveraging Internet and big data technologies is crucial for traditional industries to innovate and digitally transform, ensuring efficient information flow and meeting diverse user needs. China's network freight platforms enhance vehicle and goods search efficiency by integrating scattered and varied transport resources, thus reducing empty vehicle rates. However, as demands from car and cargo owners grow, there's a need for better evaluation of match outcomes and credibility assessment for both parties, which current services struggle to achieve with high adaptability and accuracy. Utilizing historical data to boost the efficiency and success of matching and recommendations is key for the freight platform's advancement amidst the big data era.

Rence information proposed a stable and satisfactory bilateral matching method under unclear preferences. Yang Binzhou et al[1] proposed a fuzzy optimization-based

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matching decision method for fairness. Wang Xinfan et al[2] constructed a multi-objective optimization model for bilateral matching with regret avoidance under fuzzy probability information. Zhang Di et al[3] considered fair bilateral matching based on TODIM, reflecting fairness through satisfaction differences. Le Qi et al[4] proposed an intuitive fuzzy set ranking function theory and matching decision method based on matching intention. Zhao Jinghua et al[5] studied interactions and decision-maker psychology, calculating product and service dominance using TODIM. They constructed a multi-objective optimization model based on matching satisfaction to find the best matching scheme. Li Jianbin et al[6]The concept of unit order processing time window was proposed, and the optimization strategy of pre-matching goods was presented, with the optimization goal of minimizing the total service cost to maximize the interests of drivers and customers. Yu Haiyan et al[7] Given the problem of low customer satisfaction in the vehicle and goods matching platform, the nearby random matching algorithm and rolling time domain perfect matching algorithm were designed for the mode of order grabbing and order delivery to solve the dynamic vehicle and goods matching model to improve customer satisfaction. Yang class[8] Used a content-based VCM approach to pair trucks with goods, recommending trucks at the owner's request. Meanwhile, methods based on mixed labels and collaborative filtering can accurately predict the ratings of drivers by shippers. Zhang[9] proposed a transport capacity resource selection model that took into account the economic interests of all parties, supply shortages, and the reasonable allocation of transport capacity resources. The model was designed to optimize the selection of transport capacity resources under multiple conditions, particularly considering the constraint of the supply time window. Wang class[10]Based on the attributes of various vehicles and considerable goods, considered the goods preference matrix of vehicle types. A stable matching model was established based on the preference matrix to maximize the platform revenue. Cai Yue et al[11]. addressed the scale problem in vehicle-goods matching by transforming the supply and demand matching problem into a dual sequence decision problem. They trained a dual-pointer network using the Actor-Critic algorithm to enhance the solving efficiency. Ni Shaoquan et al[12], based on considering the interests of both vehicles and goods, the platform demand was introduced, and the multi-objective optimization model was solved with the improved genetic algorithm. Mou Xiangwei et al[13]Described the goal of the car and goods matching problem and design an improved quantum evolution algorithm to enhance the efficiency of freight supply and demand matching. Tian et al[14]proposed a goods matching algorithm that utilized an improved dynamic Bayesian network.Lin Yang et al[15]Considered that the matching subject will give vague preference information, a bilateral matching method with stability and satisfaction was proposed under the intuitive unclear preference information.

In the previous study of network freight platforms, mainly from the perspective of matching satisfaction and the overall stability of the bilateral matching model, the classical bilateral matching theory hypothesis matching subject is entirely rational, and getting the matching results of one party subject satisfaction is higher. In contrast, the other side of the subject satisfaction is a low imbalance matching phenomenon. The matching subjects mostly show limited and rational behavior characteristics in vehicle and goods matching. This paper conducts the index selection of car and goods matching and establishes a complete multi-index interactive evaluation system according to the characteristic classification. At the same time, the interaction evaluation is blurred by the intuitive fuzzy rough set algorithm to highlight the objectivity of the data information. The matching recommendation optimization model is established to solve the model through multi-attribute unclear decisions to maximize overall satisfaction. It provides theoretical support and solutions for the research of vehicle and goods matching and recommendation problems and improves the operation efficiency of the freight market.

2 SELECTION AND CALCULATION OF INTERACTION EVALUATION INDICATORS

Network freight platform uses a bilateral matching system considering carrier and shipper requirements. An intelligent system designed for multi-index recommendation is detailed. Parties post info, processed into indicators, then recommended based on satisfaction levels. The premise of the platform matching optimization is to determine the evaluation index system, and the analysis of the index system will directly affect the satisfaction of the matching parties to the platform matching results. Based on the actual scores of car owners and cargo owners, this paper establishes and calculates the evaluation index system of matching subject in the process of bilateral matching.

2.1 Construction of the Index System

To be closer to the actual situation recommended by the network freight platform, due to the different priorities of the shippers and the car owners in the interaction evaluation and the other importance of the same index for the matching parties, this paper abstracts each index through mathematical models.

This paper selects several indexes as matching criteria according to the interaction evaluation information data. According to the characteristics of the index, the primary index and the expected index can be analyzed to construct a comprehensive multi-index matching system under the interactive evaluation information.

2.2 Basic Index Measurement

The primary index is an indispensable and complex standard for bilateral matching, which directly determines the capacity pool and order pool of each matching and affects the satisfaction of both sides. Firstly, the matching degree of the primary index is calculated, and the matching capacity pool and the order pool are primarily screened. The matching information that does not meet the conditions is eliminated. Those that meet the requirements will remain in the matching database. Fundamental indicators include truck type, load, starting place, destination, etc.

(1) Model type indicators. K1 means that when the truck type by the shipper is consistent with the truck owner's vehicle type, the matching degree of both parties is 1, and

the platform continues to determine other conditions; if not, the matching degree is 0, and this information will be excluded from the match.

(2) Weight index, vehicle length index, volume index. When $m = 2、3、4$, K_m represents load, vehicle length, and volume indexes, respectively. When the weight, size, and volume of the goods are less than or equal to the rated load, vehicle length, and importance of the vehicle, the satisfaction is calculated as the closeness of both, and the information of both parties shall be kept for inspection according to the remaining conditions; if the goods information exceeds the vehicle limit, the judgment value is 0, and the relevant information shall be deleted.

(3) Start-up site indicators. In the matching condition, if the starting place of the goods provided by the shipper is the same as the truck owner's current location, the matching degree of this index is 1; otherwise, it is 0.

(4) Index of the destination. When the index value of the goods owner's transportation delivery is placed in the truck owner's preference sorting set b_i^6, the matching degree is 1; otherwise, it is 0.

(5) Delivery date index. The shipper is given a hard delivery window, if the truck owner can accept the start delivery time within the delivery window, then the matching degree is 1; otherwise, it is 0.

2.3 Calculation of Expectation Type Index

Expected index refers to the index that users hope or value more from their standpoint. The higher the value of this index, the higher the user satisfaction. Among them, the distribution price index contradicts the price expectation of different matching subjects. The scores of the other users form the credibility and familiarity indicators. Because the freight platform is subject to the constraints of the evaluation mechanism, the user's scores cannot fully represent their accurate idea, and the "limited rationality" of the user will lead to the problem of data ambiguity and data absence.

In this paper, we introduce the intuition index, blur the original data with membership, non-membership, and hesitation, and calculate the similarity of the intuitive fuzzy set to determine the index's final scores to enhance the index's comprehensiveness and reliability. A_i^* and B_i^* respectively indicate the satisfaction of the shipper and the truck owner of the matching object after blurred data. A_i^* and B_j^* are intuitive fuzzy rough sets, the μ_{ij}^f is membership degree indicating satisfaction with the index f. The γ_{ij}^f is non-membership degree shows the degree of dissatisfaction with the index f, The π_{ij}^f is the intuition index, meaning the degree of hesitation to the index f.

Expected index score. (1) Distribution price index. Shippers view distribution price as a cost-type index where lower values are preferable, while truck owners see it as a benefit index where higher values are better. The variation method involves normalizing the intuitive fuzzy set of distribution prices. Each dataset is normalized with a minimum membership value of 0 and a maximum value of 1, with intermediate values inserted linearly. This normalization process allows for relative evaluation values between domain objects. The intuitive fuzzy measure of distribution price is thus determined by these principles.

(2) Credit index. The credit index is determined by mutual scores from both parties on the platform, rated across different categories. The shipper evaluates the truck owner on three aspects: completeness of type I vehicle (license and equipment), transportation services of type II (capacity and vehicle details), and service level of type III (timely/accurate delivery, damage compensation). The truck owner rates the shipper on inventory capacity (utilization, compliance) and service level (information, license). Each score is converted to fuzzy data.

$$\mu_{ij} = \sum \mu_{ij}(f)/n \tag{1}$$

$$\gamma_{ij} = \sum \gamma_{ij}(f)/n \tag{2}$$

(3) Familiarity index. The familiarity index is crucial for safe and efficient transportation matching. To ensure safety and efficiency, a user-based collaborative filtering approach is used to assess familiarity between users. The process involves identifying subject sets with similar requirements, selecting matching objects with high reputation from historical data, and calculating the similarity between historical and current schemes. Higher similarity indicates greater familiarity and a higher familiarity index.

$$SD(H,O) = 1 - D(H,O) = 1 - \left\{ \frac{1}{2} \sum_{f=1}^{t} w^f \left[\alpha\left(\mu_H^f - \mu_O^f\right)^2 + \beta\left(\gamma_H^f - \gamma_O^f\right)^2 + \lambda\left(\gamma_H^f - \gamma_O^f\right)^2 \right] \right\}^{1/2} \tag{3}$$

Among them, $w^f \in [0,1]$ $f = 1,2,\cdots,t$ $\sum_{f=1}^{t} w^f = 1$ represents the weight of different attributes or features. Generally take $w^f = 1/n$, $\alpha, \beta, \lambda \in [0,1]$ to represent the weight of the difference in membership, non-membership, and intuition index.

SD represents the degree of similarity, and the matching subject. ϕ indicates the subject's interest in the matching object. The calculation is the familiarity index as follows:

$$s(i,y) \leftarrow \sum_{z=1}^{n} SD(i,i^*) \times \phi(i^*,y) \tag{4}$$

3 MODEL SOLUTION

The multi-attribute fuzzy decision method based on an intuitive fuzzy rough set can give a comprehensive recommended evaluation value for multiple users and effectively overcome the defect of the single membership function of the fuzzy set. Therefore, this paper solves the model based on an intuitive fuzzy set and clarifies the multi-attribute decision scheme for vehicle-goods matching.

In the alternative scheme of the goods owner S_j and the truck owner R_i, select $S^+ = \left(\delta_j^{1+}, \delta_j^{2+}, \cdots, \delta_j^{f+}, \cdots, \delta_j^{t+}\right)$ and $R^+ = \left(\delta_i^{1+}, \delta_i^{2+}, \cdots, \delta_i^{f+}, \cdots, \delta_i^{t+}\right)$ that meets 100% of the user's requirements and negative ideal scenario that does not meet the requirements of the user 100%. $\delta^{f+} = (\mu^{f+}, \gamma^{f+})$ $\delta^{f-} = (\mu^{f-}, \gamma^{f-})$ $0 \le \mu^{f+} + \gamma^{f+} \le 1$ $0 \le \mu^{f-} + \gamma^{f-} \le 1$ $i = 1, 2, \cdots, m$ $j = 1, 2, \cdots, n$.

For an intuitively fuzzy ideal solution,

$$S^+ : \delta_j^+ = \begin{cases} \mu_j^+ = \max \mu_{ij(\theta)} \\ \gamma_j^+ = \min \gamma_{ij(\theta)} \\ \pi_j^+ = 1 - \mu_j^+ - \gamma_j^+ \end{cases} \tag{5}$$

For the intuitive fuzzy negative excellent scheme,

$$S^- : \delta_j^- = \begin{cases} \mu_j^- = \min \mu_{ij(\theta)} \\ \gamma_j^- = \max \gamma_{ij(\theta)} \\ \pi_j^- = 1 - \mu_j^- - \gamma_j^- \end{cases} \tag{6}$$

Suppose there are multiple positive ideal solutions δ^+ or negative ideal solutions δ^- in the candidate solution. In that case, the perfect solution is treated with incomplete certainty, considering the uncertainty of the candidate solution for multi-attribute indicators. Information is incomplete determined the protocol is defined as follows:

$$U_S = \sum_{j=1}^{n} \pi_{ij(\theta)} \Big/ n \tag{7}$$

$$U_R = \sum_{i=1}^{m} \pi_{ij(\varphi)} \Big/ m \tag{8}$$

Among them, the larger the U, the more uncertain the corresponding intuition-based fuzzy candidate solution.The distance between the alternative and the intuitive fuzzy ideal scheme $D_j^+\left(R_j^*, R^+\right), D_i^+\left(S_i^*, S^+\right)$ and between the choice and the intuitive unclear negative excellent plan $D_j^-\left(R_j^*, R^-\right), D_i^-\left(S_i^*, S^-\right)$.

Calculate the recommendation evaluation index ξ of the candidate scheme and rank the recommendation evaluation index from large to small. The larger the ξ_j value is, the more worthy it is, which is specified as follows:

$$\zeta_j = D_j^- \Big/ D_j^+ + D_j^- \tag{9}$$

The multi-attribute fuzzy decision algorithm based on an intuitive fuzzy rough set is described as follows:

Step 1: Organize the intuitive fuzzy data in the candidate scheme into a decision matrix $P_{(\theta)}$. Based on the decision matrix $P_{(\theta)}$, the weighted normalized matrix $Z_{(\theta)}$ can be obtained by combining different attributes' weights w^f.

Step 2: Select the candidates' unique and damaging ideal schemes. In the calculation process, if multiple excellent schemes or negative perfect schemes occur, the incomplete uncertainty is calculated, and the system is transparent

Step 3: Calculate the distances $D_j^+(S_j^*, S^+)$ and $D_j^-(S_j^*, S^-)$ between the candidate scheme and the ideal S^+ and negative ideal scheme S^-.

Step 4: Calculate the recommended evaluation index ξ_j of each candidate scheme according to formula and rank it; the one with the most significant value is the most recommended.

4 NUMERICAL EXPERIMENTS

4.1 Analysis of the Results

After controlling for the number of users and the number of projects, after many experiments and sorting out the data, the satisfaction comparison before and after optimization was obtained, as shown in Table 1.

Table 1. Comparison of matching satisfaction

Optimized matching satisfaction	Match satisfaction before optimization	Satisfaction gap	Optimize the range
36.89	27.25	9.64	35.38%

At the same time, this paper analyzes the real-time feedback of users to the dynamic recommendation. It randomly selects 140 users from two network freight platforms as the verification set to calculate their satisfaction with the recommended results. The calculation of happiness is random, as shown in Figure1 In this case, the overall satisfaction of Platform A is maintained at 60% or above, and the joy of more than 80% accounts for 50% of the total number.

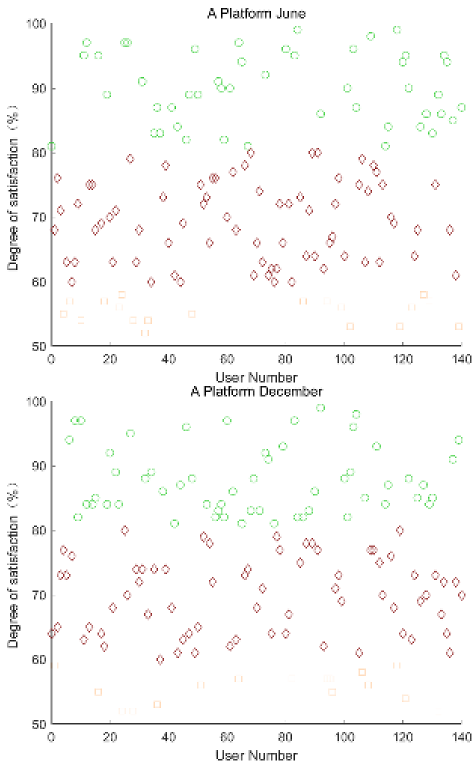

Fig. 1. Random user satisfaction

5 CONCLUSION

This paper delves into enhancing vehicle and goods matching in the network freight market by introducing evaluation indices for collaborative filtering recommendation algorithms. It establishes intelligent matching index systems and models for shippers and truck owners to boost matching efficiency and satisfaction while addressing data loss and personalized recommendation challenges. Key conclusions include clarifying preferences and demands, calculating expected indices via collaborative filtering, and creating a comprehensive matching index system. Additionally, a matching recommendation model is developed to optimize satisfaction for both parties by incorporating non-membership, intuitive indices, and prospect theory. The study proposes a solution based on intuitive fuzzy multi-attribute decision-making to tackle challenges like multi-indicators, multi-weights, and multi-users, ultimately improving recommendation accuracy and enhancing matching efficiency in the transport capacity pool.

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