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Improve GMRACCF Qualifications via Collaborative Filtering in Vehicle Sales Chain

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Abstract: The Vehicle Allocation Problem (VAP) in the vehicle sales chain has three bottlenecks in practice. The first is to collect relevant cooperation or conflict information, the second is to accurately quantify and analyze other factors affecting the distribution of cars, and the third is to establish a stable and rapid response to the vehicle allocation management method. In order to improve the real-time performance and reliability of vehicle allocation in the vehicle sales chain, it is crucial to find a method that can respond quickly and stabilize the vehicle allocation strategy. Therefore, this paper addresses these issues by extending Group Multi-Role Assignment with Cooperation and Conflict Factors (GMRACCF) from a new perspective. Through the logical reasoning of closure computation, the KD45 logic algorithm is used to find the implicit cognitive Cooperation and Conflict Factors (CCF). Therefore, a collaborative filtering comprehensive evaluation method is proposed to help administrators determine the influence weight of CCFs and Cooperation Scales (CSs) on the all-round performance according to their needs. Based on collaborative filtering, semantic modification is applied to resolve conflicts among qualifications. Large-scale simulation results show that the proposed method is feasible and robust, and provides a reliable decision-making reference in the vehicle sales chain.

Key words: Vehicle Allocation Problem (VAP); Group Multi-Role Assignment with Cooperation and Conflict Factors (GMRACCF); KD45 logic algorithm; collaborative filtering; semantic modification; Cooperation and Conflict Factors (CCFs); Cooperation Scale (CS)

1 Introduction

The Chinese vehicle market is currently one of the largest in the world, making the profit from the domestic market crucial for Chinese automakers. In the vehicle industry chain, automakers and dealers collaborate closely, but the Vehicle Allocation Problem (VAP) has become an unavoidable issue due to the differences in consumer demand and purchasing power across cities. Most automakers sell their cars primarily in city clusters near their manufacturing sites, causing consumers in other regions to either wait long periods or pay high fees. Therefore, there is an urgent need for a strategy that can meet the needs of consumers in different regions while ensuring profitability for automakers.

However, implementing such a strategy faces three practical bottlenecks. The first is the collection of relevant cooperation or conflict information. The second is accurately quantifying and analyzing other factors that influence vehicle distribution. And the third is establishing a stable and rapid vehicle allocation management method.

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VAP is a many-to-many allocation problem between an automaker and a city dealer. This implies that an automaker can sell cars to different city dealers, and city dealers can accept cars from multiple automakers at the same time. It is important to note that automakers may have different preferences, and market preferences may vary across cities. Additionally, cooperation and competition among automakers are common in this context.

This paper attempts to formalize and model the VAP using Group Multi-Role Assignment with Cooperation and Conflict Factors (GMRACCF). It is an extended form of Group Multi-Role Assignment (GMRA)[1, 2] and an important step of Role-Based Collaboration (RBC)[3–7]. By modeling this problem, the vehicle allocation problem of automakers and vehicle dealers can be effectively solved, but it does not address the three bottlenecks that are common in the vehicle sales chain.

A new collaborative filtering method is proposed to solve the proposed problems in this paper. Firstly, we use the KD45 algorithm to mine the original Cooperation and Conflict Factors (CCFs) matrix. For the cooperation and conflict relationships between automakers, the KD45 algorithm can better improve and explore more CCF matrices, and can improve the GMRACCF model to provide a more precise and suitable vehicle allocation strategy.

Furthermore, after using the KD45 algorithm, the scale of historical cooperation is a crucial factor that affects car supply for both automakers and car dealers. Automakers are more likely to offer maximum concessions to dealers with a large historical cooperation scale in order to increase their own profits. This mutually beneficial relationship highlights the importance of cooperation scale. In addition, it is necessary to measure the impact of CCF and Cooperation Scale (CS) by assigning weight values based on the commercial support and market preference of different automakers in various cities. The introduction of weights allows administrators to adjust the weight values more accurately according to the specific requirements. This is why collaborative filtering plays a significant role.

Finally, to enhance the accuracy and perfection of the qualification matrix, it is necessary to adjust the threshold of KD45 due to possible anomalies in the CCF matrix with the KD45 logic algorithm. Introducing a cooperation threshold among automakers helps resolve conflicts in partial Q-values and enables the decision maker to formulate a more precise vehicle allocation strategy based on demand.

With regards to the allocation of vehicles in the sales chain, the simulation results indicate that the model is not only applicable to the vehicle allocation problem, but can also be extended to various many-to-many assignment problems within the sales chain.

The contributions of this article include:

(1) Through the extension of GMRACCF, the VAP of automakers is formalized into the VAP of several automakers.

(2) To ensure the stability of the supply for automakers and city dealers, this paper presents a process for cooperation scale and considers this process as a feedback mechanism for GMRACCF.

(3) Through allocation, vehicles from various automakers can be assigned to different city car dealerships, allowing for quick adjustments to the vehicle allocation plan based on the strategy. The simulation results serve as a valuable reference for vehicle sales chain administrators.

This article is organized as follows. It describes a real-world scenario to illustrate the problem in Section 2. The problem is then formally defined through GMRACCF in Section 3. In Section 4, an extended GMRACCF based on cooperative filtering and semantic modification is proposed. The results of large-scale simulation experiments are shown in Section 5. Section 6 introduces the related research work. The prospect of the future and the conclusion of this paper are given in Section 7.

2 Real-World Scenario

Organization X is specialized in the study of vehicle sales chains. Ann, the CEO, wants to study the distribution of cars and establish a new distribution management center. She asked Bob, the CTO, to do so based on historical data. Then, Bob recognizes that it is a typical assignment problem, i.e., GMRA[8]. He lists the number of automakers required by dealers in each city according to demand, as shown in Table 1.

At the same time, Bob also searches for the right automakers for the city dealer. The automakers are selected based on their previous vehicle distribution performance. After that, Bob evaluates the ability of each automaker to supply cars to the city according to the past performance of these automakers[8] (see Table 2).

Table 1 Number of automakers required by city vehicle dealers.

City vehicle dealer	Number of automakers required
D1	2
D2	1
D3	2
D4	1
D5	3
D6	1
D7	2
D8	1
D9	2
D10	3

Table 2 Maximum number of cities supplied by automakers.

Automaker	Maximum number of cities required
A1	6
A2	9
A3	3
A4	5
A5	3
A6	1
A7	2
A8	1

In light of the presence of commercial cooperation and competition among certain automakers, such as Guangzhou Automobile Group (GAC) Co., Ltd. and Shanghai Automotive Industry Corporation (SAIC) Co., Ltd., respectively, conflicts arise among these automakers due to their different market preferences in the two cities. However, since both Guangzhou and Foshan are situated in the Pearl River Delta region, they share similar market preferences towards GAC Co., Ltd., resulting in a cooperative relationship between the automakers. Now, Bob finds that the problem has the properties of Group Role Assignment (GRA) with CCF (GRACCF)[9].

In order to enhance the sustainability and balance of the new vehicle allocation strategy and follow the formalization of a GRACCF problem, Ann and Bob collaborate with the current vehicle allocation administrators during the process of assigning urban dealerships to automakers. The administrators share that some automakers have demonstrated both cooperative and conflicting intentions on various projects. To address this, Ann mandates that the administrators gather information on all instances of cooperation or conflict between automakers. The administrators distribute questionnaires to collect these details, which are summarized in Table 3. In Table 3, a value of 0 indicates no conflict or cooperation, values less than 0 indicate conflict, and values greater than 0 indicate cooperation. The values of other automaker-dealer pairs not in Table 3 are all 0. The value of the first row and third column in Table 3 is −0.30, this indicates that when Automaker A1 supplies vehicles to Dealer D2, Automaker A1 also supplies vehicles to Dealer D6, resulting in a conflict relationship. The conflict value is –0.3.

Table 3 CCFs.

Automaker-Dealer	A1-D2	A1-D3	A1-D6	A1-D7	A1-D8	A2-D8	A2-D9	A2-D10	A3-D1	A3-D2	A3-D4	D5-D5	D5-D7	D6-D1	D6-D2
A1-D2	0.00	0.00	–0.30	0.35	0.35	0.00	0.00	0.00	–0.40	0.00	0.00	0.00	0.00	0.80	0.90
A1-D3	0.00	0.00	–0.20	–0.20	0.20	0.00	0.00	0.00	–0.50	0.00	0.00	0.00	0.00	0.50	0.60
A1-D6	–0.20	0.20	0.00	0.00	0.00	0.20	0.20	0.30	0.00	0.00	0.00	–0.30	0.35	0.70	0.60
A1-D7	–0.35	–0.20	0.00	0.00	0.00	0.20	0.20	0.30	0.00	0.00	0.00	–0.20	–0.20	0.00	0.00
A1-D8	0.35	0.40	0.00	0.00	0.00	0.20	0.20	0.20	0.00	0.00	0.00	–0.30	0.35	0.00	0.00
A1-D8	0.00	0.00	0.20	0.20	0.30	0.00	0.00	0.00	–0.50	–0.40	–0.30	0.00	0.00	0.60	0.70
A1-D9	0.00	0.00	0.20	0.20	0.30	0.00	0.00	0.00	–0.40	–0.45	–0.30	0.00	0.00	0.00	0.00
A1-D10	0.00	0.00	0.20	0.20	0.20	0.00	0.00	0.00	–0.20	–0.20	–0.30	0.00	0.00	0.00	0.00
A3-D1	0.00	0.00	0.00	0.00	0.00	0.30	0.20	0.30	0.00	0.00	0.00	0.00	0.00	0.80	0.70
A3-D2	0.00	0.00	0.00	0.00	0.00	–0.40	–0.45	–0.20	0.00	0.00	0.00	0.00	0.00	0.60	0.60
A3-D4	0.00	0.00	0.00	0.00	0.00	–0.20	–0.20	–0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A5-D5	0.30	0.20	–0.30	0.35	0.35	0.30	0.20	0.10	–0.50	–0.40	–0.30	0.00	0.00	0.70	0.70
A5-D7	0.00	0.00	–0.20	–0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.60
A6-D1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	–0.40	0.00	0.00	0.80	0.60	0.00	0.00
A6-D2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	–0.30	0.00	0.00	0.80	0.60	0.00	0.00

The purpose of this questionnaire is to establish a long-term cooperative vehicle allocation strategy. It is important to consider the cooperation and conflict among team members as it directly affects the interests of the respondents. It is assumed that there is no bias in the obtained questionnaire results[10–12].

Bob assures that the E-CARGO model, along with its extension, the GRACCF model, has proven to be an efficient solution for addressing the resource allocation problem, particularly in considering the CCFs among automakers. Motivated by this, Bob decides to utilize these models to tackle the vehicle allocation problem. He follows the steps outlined in the GMRA and GRACCF model, and successfully obtains the allocation results for the vehicles.

Furthermore, Bob presents his statistics to Ann and shares the assignment results of the new vehicle allocation strategy obtained by GRACCF. However, Ann expresses dissatisfaction with the outcome of this assignment and highlights three issues. Firstly, Ann finds Bob's method of obtaining results to be overly complicated and suggests finding a new approach by combining GMRA and GRACCF to achieve vehicle allocation results. Then, Ann observes that Table 3 represents a sparse matrix, neglecting potential relationships that could significantly impact the efficiency of vehicle allocation. Thus, Ann expects Bob to not only identify potential relationships among automakers, but also quantify the relationship between CS and CCFs. This will enable the formation of a sustainable team that meets expectations. Finally, Ann wants Bob's vehicle allocation to be able to promptly and accurately respond to different policies, whether they are loose or strict, while also addressing the cooperation and conflict relationships. Now, Bob encounters new challenges in his research, including the following:

(1) To obtain car allocation results, a novel approach can be adopted by integrating GMRA and GRACCF methodologies.

(2) The questionnaire he is using is incomplete, and he needs to extract information regarding potential cooperation or conflict.

(3) He requires a clear understanding of the quantitative relationship between CS and CCFs.

(4) He is in search of a vehicle allocation method that can quickly adapt to a loose or strict policy, and also rectify the relationship between cooperation and conflict.

Fortunately, we can address these issues by redefining GMRACCF and expanding upon the existing GMRACCF framework. The upcoming sections elaborate on the specifics of our proposed solution, which can greatly assist Bob in facing the above challenges.

3 Problem Formalization with E-CARGO Model

To solve the VAP, we first formalize it by revising the E-CARGO model and its extended model GMRACCF. In the following descriptions, we clearly put citations to the definitions presented in the previous work. Those definitions without citations are coined for the first time or modified in this paper.

With the E-CARGO model[13–17], the system can be described as a 9-tuple $\sum ::= < \mathcal{C}, \mathcal{O}, \mathcal{A}, \mathcal{M}, \mathcal{R}, \mathcal{E}, \mathcal{G}, S_0, \mathcal{H} >$, where $\mathcal{C}$ is a set of classes, $\mathcal{O}$ is a set of objects, $\mathcal{A}$ is a set of agents, $\mathcal{M}$ is a set of messages, $\mathcal{R}$ is a set of roles, $\mathcal{E}$ is a set of environments, $\mathcal{G}$ is a set of groups, S_0 is the initial state of the system, and $\mathcal{H}$ is a set of users. In such a system, $\mathcal{A}$ and $\mathcal{H}, \mathcal{E}$ and $\mathcal{G}$ are tightly coupled sets. Every group should work in an environment. An environment regulates a group.

When discussing role assignment problems[18, 19], it is common to simplify environments and groups into vectors and matrices, respectively. Furthermore, we use nonnegative integers $m = (|\mathcal{A}|$, which is the cardinality of set $\mathcal{A}$), to express the size of the agent set $\mathcal{A}$, and $n = |\mathcal{R}|$, which is the size of the role set $\mathcal{R}$. The indices of agents and roles are denoted by $i \in \{0, 1, \ldots, m-1\}$ and $j \in \{0, 1, \ldots, n-1\}$.

Here, we use the real-world scenario mentioned in Section 2 as an example to describe RBC and its extended GMRACCF model better. The VAP can be defined in the following manner.

Definition 1 A role[3–5] is defined as $r ::= <\text{id}, ® >$ where id is the identification of r and ® is the set of requirements of properties for agents to play r.

Note: In the VAP, the role is the city dealer who has a demand for the car. Therefore, ® represents the number of automakers required by the corresponding dealer.

Definition 2 An agent[20] is defined as $a ::= <\text{id}, ⓠ>$, where id is the identification of a, ⓠ represents the set of a's values corresponding to the abilities required in the group.

Note: In the scenario, the agent refers to the automakers and ⓠ represents the agent's historical representation of ®.

Definition 3 A role range vector L[1] is a vector of the lower bound of the ranges of roles in environment e of group g.

Note: L is a valuable component in the E-CARGO model. It represents the minimum number of automakers that dealers in each city need to supply cars. As can be seen from Table 1, $L = [2\,1\,2\,1\,3\,1\,2\,1\,2\,3]$.

Definition 4 An ability limit vector L^{a}[18] is an m-dimensional vector, where $L^{a}[i]\ (0 \leqslant i < m)$ indicates the maximum number of dealerships each automaker can supply vehicles to. The superscript of L^{a} indicates that L^{a} is a definition for the agents.

Note: Due to the different economic strength, the supply capacity of automakers is different and limited. For example, in our scenario, as shown in Table 2, L^{a} represents the maximum number of dealers that each automaker can supply vehicles to. As can be seen from Table 2, $L = [6\,9\,3\,5\,3\,1\,2\,1]$.

Definition 5 A preference matrix P is an $m \times n$ matrix, where $P[i, j] \in [0, 1]$ expresses the preference value of agent i $(0 \leqslant i < m)$ for role $j\,(0 \leqslant j < n)$. $P[i, j] = 0$ indicates the lowest value and 1 the highest.

Note: It indicates that the preference of city vehicle dealers for automakers is primarily determined through standardization based on factors, such as local income, consumption level, and logistics distance.

Definition 6 A preference index matrix P^{a} is an $m \times n$ matrix, where $P^{a}[i, j] \in [0, 1]$ expresses the preference value of agent $i\,(0 \leqslant i < m)$ for role $j\,(0 \leqslant j < n)$. $P^{a}[i, j] = 0$ indicates the lowest value and 1 the highest.

Note: It indicates that the preference of automakers for city dealers is primarily determined through standardization based on local sales levels, logistics costs, and other relevant factors.

Definition 7 A criteria evaluation matrix C is an $m \times n$ matrix, where $C[i, j] \in [0, 1]$ is a vector that expresses the values of quantitative criteria when agent i is supplied to role j.

Note: Represents the ability of automakers i (agent i) to provide vehicles to city vehicle dealer j (role j) after normalization based on the market share of automakers in cities.

Definition 8 A qualification matrix Q[3] is an $m \times n$ matrix, where $Q[i, j] \in [0, 1]$ expresses the qualification value of agent $i\,(0 \leqslant i < m)$ for role $j\,(0 \leqslant j < n)$. $Q[i, j] = 0$ indicates the lowest value and 1 the highest.

Note: Q matrix is the result of the agent evaluation step of RBC. It can be obtained by comparing all the qualifications of agents with all the requirements of roles. In this article, since PuLP's[21] assignment method is already available, creating Q is our main concern. Note that the relevant Q matrix in the VAP requires some corrections, especially if the criteria for measuring the allocation of vehicles is subject to a variety of influences. While certain quantitative indicators have been suggested to evaluate automakers based on historical sales data, other significant factors, such as logistics costs and car prices, have not been taken into account. Additionally, the preferences of automakers and city dealers in evaluation criteria significantly impact the sustainability of vehicle allocation. Therefore, we propose a more comprehensive agent evaluation method to create Q matrix.

Definition 9 Given C, P^{a}, and P, the VAP is a GRACCF problem, where Q is formed by

$$Q[i, j] = P^{a} \circ C \circ P,\ 0 \leqslant i < m,\ 0 \leqslant j < n \tag{1}$$

where P^{a} denotes agent i's preference for the role j, and P represents the role j's preference for agent i. The symbol "$\circ$" represents the Hadamard product of matrix. Since the values of matrices C, P^{a} and P are independent and identically distributed, we use the Weighted Sum (WS) method to quantify Q[2], because WS is well accepted to combine many numerical factors together to form one numerical indicator. Equation (1) aims to establish a more reasonable evaluation standard by taking into account the preferences of agents and roles towards the aforementioned criteria.

Definition 10 A compact CCF matrix C^{cf}[10] is an $n_{\mathrm{c}} \times 5$ matrix, where $C^{\mathrm{cf}}[k, 4] \in [-1, 0) \cup (0, 1]$ $(0 \leqslant k < n_c)$ expresses that the degree of cooperation or conflict effect when agent $C^{\mathrm{cf}}[k, 0]$ plays role $C^{\mathrm{cf}}[k, 1]$ and agent $C^{\mathrm{cf}}[k, 2]$ plays role $C^{\mathrm{cf}}[k, 3]$. n_{c} represents the total number of nonzero elements in C^{cf}.

Definition 11 A role assignment matrix T is defined as an $m \times n$ matrix, where $T[i, j] \in \{0, 1\}\ (0 \leqslant i < m,\ 0 \leqslant j < n)$ indicates whether or not agent i is supplied to role j. $T[i, j] = 1$ means yes and 0 for no.

Definition 12 A CCF assignment vector $\overline{T}$ is an n_{c}-vector, where $\overline{T}[k] \in \{0, 1\}\ (0 \leqslant k < n_{\mathrm{c}})$ indicates whether or not cooperation or conflict factor $\overline{T}[k]$ is chosen. $\overline{T}[k] = 1$ means yes and 0 means no.

Definition 13 The group performance $\sigma^{\mathrm{GMRACCF}}$ of Group (g) is defined as the sum of the assigned agents' qualifications, that is

$$\sigma^{\text{GMRACCF}}(T)=\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}Q[i,j]\times T[i,j]+\left[\sum_{k=0}^{n_c-1}C^{\text{cf}}[k,4]\times Q\left[C^{\text{cf}}[k,0],\ C^{\text{cf}}[k,1]\right]\times\overline{T}[k]\right].$$

Note: The social meaning of σ^{GMRACCF} is the team performance when considering the impact of CCFs. The first part on the right side of the equation represents individual performance, while the second part represents the benefits of CCFs' impacts.

Definition 14 Role j is workable[1] in Group (g) if it has been assigned enough agents, that is

$$\sum_{i=0}^{m-1}T[i,j]\geqslant L[j],\ 0\leqslant j<n.$$

Definition 15 T is workable if each role j is workable[1], Group g is workable if T is workable. From the above definitions, Group (g) can be expressed by L, L^{a}, Q, C^{cf}, T, and $\overline{T}$,

$$\sum_{i=0}^{m-1}T[i,j]=L[j],\ 0\leqslant j<n.$$

Definition 16 Given Q, L, L^{a}, and C^{cf}, the GMRACCF problem is to find a workable T,

$$\sigma^{\text{GMRACCF}}(T)=\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}Q[i,j]\times T[i,j]+\left[\sum_{k=0}^{n_c-1}C^{\text{cf}}[k,4]\times Q\left[C^{\text{cf}}[k,0],C^{\text{cf}}[k,1]\right]\times\overline{T}[k]\right],$$

subject to

$$T[i,j]\in\{0,1\},\ 0\leqslant i<m,0\leqslant j<n \tag{2}$$

$$\sum_{i=0}^{m-1}T[i,j]=L[j],\ 0\leqslant j<n \tag{3}$$

$$\sum_{j=0}^{n-1}T[i,j]\leqslant L^{\text{a}}[i],\ 0\leqslant i<m \tag{4}$$

$$\overline{T}[k]\in\{0,1\},\ 0\leqslant k<n_c \tag{5}$$

$$2\overline{T}[k]\leqslant T[C^{\text{cf}}[k,0],C^{\text{cf}}[k,1]]+T[C^{\text{cf}}[k,2],C^{\text{cf}}[k,3]],\ 0\leqslant k<n_c \tag{6}$$

$$T\left[C^{\text{cf}}[k,0],C^{\text{cf}}[k,1]\right]+T\left[C^{\text{cf}}[k,2],C^{\text{cf}}[k,3]\right]\leqslant\overline{T}[k]+1,\ 0\leqslant k<n_c \tag{7}$$

where Formulas (2)–(4) are the constraints for the control variables $T[i,j]$. where expressions Formulas (5)–(7) are the constraints for the vector $\overline{T}$.

Now, the vehicle allocation problem can be formulated as a linear programming problem like Definition 11. To solve this problem, we can utilize the PuLP linear programming tool kit[21], which is an industry-standard optimization tool. PuLP is an open-source package in Python. By using PuLP, we calculated the optimal group performance $\sigma^{\text{GMRACCF}}(T)$ to be 18.38.

4 Extended GMRACCF Model

As mentioned above, there are still three important bottlenecks in the practical application of the GMRACCF model. The first is that the distribution result is affected by the potential CCF among automakers due to the sparse CCF matrix. Thus, more CCF needs to be mined. The second is that the objective function of GMRACCF should not only consider the relationship between cooperation and conflict, but also take into account the impact of cooperation scale. This makes it difficult for administrators to distinguish between the relationship between CCFs and the impact of CS. The third is the need for a way to quickly and accurately respond to different policies, whether they are lax or strict, and to correct cooperative and conflicting relationships accordingly. To address these issues, this section briefly introduces the KD45 logic algorithm used in Ref. [22], which can identify potential CCFs. Additionally, a collaborative filtering evaluation method is designed to assist administrators in determining the impact weights of CCFs and CS on team performance as required. Finally, semantic modification is applied to address conflicts in the original part based on collaborative filtering.

4.1 KD45 logic algorithm

The constraint matrix used in vehicle allocation is obtained from a voluntary questionnaire filled by automakers. This method of obtaining the matrix results in it being sparse, local, and asymmetric. The constraint matrix plays a crucial role in vehicle allocation as it helps in assigning group roles. Having a more complete constraint matrix allows for a more comprehensive consideration in the group role assignment process, leading to faster efficiency and more benefits in vehicle allocation. Mining potential CCF among automakers is essentially a relationship reasoning problem involving multiple agents. The modal logic system is an effective method for solving multi-agent relationship reasoning problems[23]. However, the KD45 logic system is widely used for multi-agent knowledge and belief representation and reasoning[24]. Hence, in this study, we apply the KD45 logic system to explore potential relationships between agents. The KD45 logic system consists of four axioms, as shown in Table 4.

(1) Axiom K is presented in relations that adhere to the semantics of Kripke relations. Axiom K is applicable to the specific context discussed in this paper.

(2) Axiom D also represents the concept of sum persistence, highlighting the interconnectedness of everything. Nothing exists in isolation, including the agent itself, which may have conflicting or cooperative relationships with other agents.

(3) Axiom 4, also known as transitivity, states that if the relationship between x and y is equivalent to the relationship between y and z, then the same relationship exists between x and z.

(4) Axiom 5, also known as the Euclidean property, states that if the same relation exists between things x and y as exists between things x and z, then the above relation also exists between things y and z.

Example: Here, we use the scenario in Section 2 as an example to illustrate that the VAP satisfies the four axioms of the KD45 logic system. In Table 3 there is a cooperation relationship: [A1-D3, A1-D8], [A1-D8, A2-D8], and [A1-D3, A6-D1]. Using Axioms 4 and 5, we can capture the implied relationship [A1-D3, A2-D8], [A1-D8, A6-D1], and [A6-D1, A1-D8]. The specific process is shown in Algorithm 1.

After applying the KD45 algorithm to extend the CCF matrix $C^{\rm cf}$ in GMRACCF, the number of conflicts and collaborations in $C^{\rm cf}$ is greater than the original one. Additionally, the group performance $\sigma(T)$ of the extended GMRACCF model is 21.58, while the original GMRACCF model achieves 18.38. The comparison clearly demonstrates that the KD45 algorithm has a significant impact on group performance, with an increase of 17% [(21.58−18.38)/18.38]. It is important to note that the original GMRACCF, which solely relies on CCFs, may have lower team performance in practical scenarios as it fails to consider implicit cooperation effects and potential conflicts. Therefore, the revised GMRACCF model is expected to yield more benefits compared to the original version.

Table 4 Main parameters in experiment.

Axiom name	Axiom	Meaning	Condition on frames
K	$\Box(A\rightarrow B)\rightarrow(\Box A\rightarrow\Box B)$	Distributive	Kriple's relational semantics
D	$\Box A\rightarrow\Diamond A$	Serial	$\forall x, \exists y \rightarrow xRy$
4	$\Box A\rightarrow\Box\Box A$	Transitive	$\forall x, y, z, xRy\wedge yRz \rightarrow xRz$
5	$\Diamond A\rightarrow\Box\Diamond A$	Euclidean	$\forall x, y, z, xRy\wedge xRz \rightarrow yRz$

Note: Symbols $\Box$ and $\Diamond$ represent necessity and possibility in modal logic, respectively, A and B are both propositions, and xRy represents that element x and y have a relationship R.

4.2 Collaborative filtering

In addition to extending the GMRACCF model, another important aspect is quantifying the relationship between CS and CCF to assist administrators in making informed decisions. To address this challenge, we introduce a collaborative filtering evaluation method. To provide a clearer understanding of this

Algorithm 1 KD45 logic algorithm

Input: $C^{\rm cf}$, $\mathcal{G}$

Output: $C^{\rm cf}_{\rm KD45}$ /* $C^{\rm cf}_{\rm KD45}$ is the CCF matrix after KD45 logic algorithm

Begin

1: $C^{\rm cf}_{\rm KD45} \leftarrow \varnothing$;

2: $C^{\rm cf}_{\rm coop}$, $C^{\rm cf}_{\rm conf} \leftarrow$ classifyRelationship ($C^{\rm cf}$);

/* Meeting the KD45 logic system, $C^{\rm cf}_{\rm coop}$ and $C^{\rm cf}_{\rm conf}$ are the cooperation matrix and conflict matrix after KD45 logic algorithm, respectively. Finding transitive closure first and then Euclidean closure can greatly avoid reflexivity*/

3: $C^{\rm cf}_{\rm coop} \leftarrow$ transitiveClosure ($C^{\rm cf}_{\rm coop}$, $\mathcal{G}$);

/* Whether $C^{\rm cf}_{\rm coop}$ satisfies Axiom 4 */

4: $C^{\rm cf}_{\rm coop} \leftarrow$ EuclideanClosure ($C^{\rm cf}_{\rm coop}$, $\mathcal{G}$);

/* Whether $C^{\rm cf}_{\rm coop}$ satisfies Axiom 5 */

5: $C^{\rm cf}_{\rm conf} \leftarrow$ transitiveClosure ($C^{\rm cf}_{\rm conf}$, $\mathcal{G}$);

/* Whether $C^{\rm cf}_{\rm conf}$ satisfies Axiom 4 */

6: $C^{\rm cf}_{\rm conf} \leftarrow$ EuclideanClosure ($C^{\rm cf}_{\rm conf}$, $\mathcal{G}$);

/* Whether $C^{\rm cf}_{\rm conf}$ satisfies Axiom 5 */

7: $C^{\rm cf}_{\rm KD45} \leftarrow$ integrateRelationship ($C^{\rm cf}$, $C^{\rm cf}_{\rm coop}$, $C^{\rm cf}_{\rm conf}$, $\mathcal{G}$);

/* The extended $C^{\rm cf}_{\rm KD45}$ matrix is obtained */

8: **Return** $C^{\rm cf}_{\rm KD45}$

end

approach, we also introduce some new definitions.

Definition 17 A cooperation scale matrix C^{S} is an $m\times n$ matrix, where $C^{\mathrm{S}}[i,j]\in[0,1]$ expresses a true qualification value considering the cooperation scale when agent i is supplied to role j. $C^{\mathrm{S}}[i,j]=1$ indicates the highest value and 0 the lowest.

Note: In considering the impact of the cooperation scale between automakers and dealers on vehicle allocation strategy, we propose a reasonable hypothesis: the cooperation scale between automakers (agents) and city dealers (roles) in the actual vehicle sales chain also influences the agents' actual performance. This can result in the actual performance being lower than what is indicated in Q. To analyze this further, it is necessary to define a matrix that represents the cooperation scale between automakers (agents) and dealers (roles) in each city dealer based on historical.

Definition 18 Weight coefficient $\omega\in[0,1]$ indicates how much administrators attach importance to the CCFs of automakers, and the coefficient $1-\omega\in[0,1]$ indicates how much administrators attach importance to the CS between automakers and city vehicle dealers.

Note: To evaluate the impact of cooperation and conflict on actual performance, we introduce the parameter ω to represent the degree of cooperation and conflict, while $1-\omega$ represents the degree of cooperation scale on actual performance.

The above Definitions 17 and 18 introduce the extended GMRACCF model as follows:

$$\sigma^{\text{CF-GMRACCF}}(T)=\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}Q[i,j]\times T[i,j]+\left[\omega\times\sum_{k=0}^{n_{\mathrm{c}}-1}C^{\mathrm{cf}}[k,4]\times Q\left[C^{\mathrm{cf}}[k,0],C^{\mathrm{cf}}[k,1]\right]\times\overline{T}[k]\right]+\left[(1-\omega)\times\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}C^{\mathrm{S}}[i,j]\times T[i,j]\right],$$

where $\sigma^{\text{CF-GMRACCF}}$ represents the team performance of the extended GMRACCF model based on collaborative filtering.

With the abovementioned Definitions 17 and 18 and constraints, we propose the group evaluation method. Here, we define additional symbols as follows to simplify our descriptions:

(1) "step" represents the increasing step of CCF weight ω. The value range of step is [0, 1]. In our scenario, we randomly set it to 0.05. Without loss of generality, we will conduct large-scale randomized experiments in Section 5.

(2) CF-GMRACCF ( ) is a function based on collaborative filtering extension GMRACCF to call the Python PuLP solution. This section presents a proposed collaborative filtering evaluation method that aims to determine the impact of CCFs and cooperation scale on team performance, as per the requirements of administrators. The extended GMRACCF model has a time complexity that is NP-hard, which also applies to the team evaluation method. However, based on experiments, it has been found that the PuLP solution[21] is a practical approach for certain scales.

The comparison between the original GMRACCF and the collaborative filtering approach, as shown in Figs. 1 and 2, reveals that changes in the CCF weight lead to corresponding changes in the team performance σ. This suggests that adjusting the weights of CCFs and CSs enable effective adjustment of the vehicle allocation strategy based on the desired level of strictness or looseness by administrators. When weight ω of CCFs increases, although the team performance σ decreases, it remains higher than when the CS is not considered. This indicates a positive impact of cooperation scale on team performance when considering cooperation and conflict. Thus, the effectiveness of the collaborative filtering method is also demonstrated.

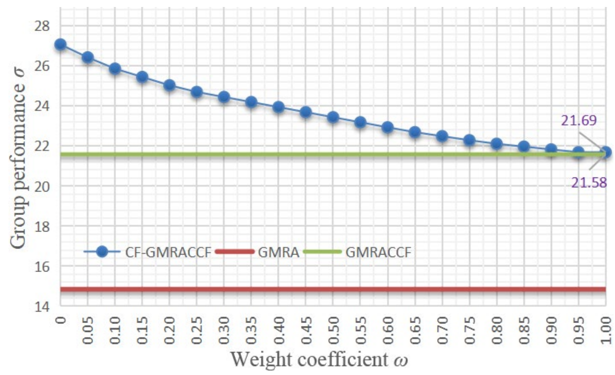

Fig. 1 Group performance with different ω values.

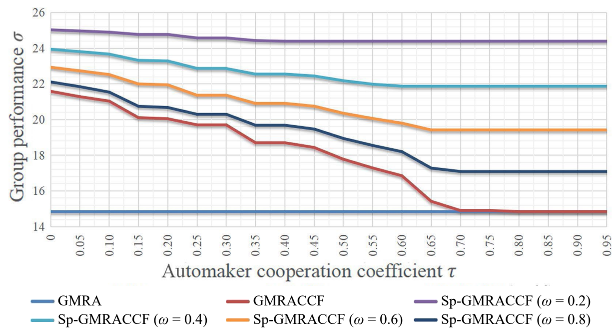

Fig. 2 Group performance with different τ values (different ω).

4.3 Semantic modification

In the previous section, we focus on collaborative filtering and examine how cooperation, conflict, and the degree of cooperation impact group performance. In this section, we aim to determine the positive impact on group performance by adjusting the threshold of cooperation and conflict. We also aim to identify an assignment method that benefits both automakers and dealers. This method will help protect their interests.

Definition 19 The automaker cooperation coefficient $\tau \in [0,1]$ represents the impact of the CCFs that administrators expect among automakers.

Note: In the case of different cooperation and conflict weights with ω values, the sales strategy adopted by the automaker becomes more open as the τ value decreases. Conversely, a larger value of τ indicates a more conservative sales strategy. As administrators prefer automakers with greater CCF influence, we introduce the automaker cooperation coefficient τ to help identify automakers with larger CCF values. To further clarify the physical meaning of τ, we provide the following Definitions 20 and 21.

Definition 20 The cooperation threshold τ_{coop} represents the degree of cooperation between the automakers expected by the administrator, $\tau_{\text{coop}} \in [0,1]$

Note: In this paper, we set $\tau_{\text{coop}} = \tau$ to find automakers with a high degree of cooperation.

Definition 21 The conflict threshold τ_{conf} denotes the degree of conflict between automakers acceptable to the administrator, $\tau_{\text{conf}} \in [0,1]$.

Note: In this paper, we set $\tau_{\text{conf}} = \tau - 1$ to find low-conflict automakers.

Here, we adopt the defined scenario to explain the meaning of τ. When the administrator sets $\tau = 0.3$, that is, $\tau_{\text{coop}} = 0.3$ and $\tau_{\text{conf}} = -0.7$. if $-0.7 < C^{\text{cf}}[i_1, j_1, i_2, j_2] < 0.3$ $(0 \leqslant i_1, i_2 < m$ and $0 \leqslant j_1, j_2 < n)$, then the relationship between them is ignored, such as [A1-D2, A3-D1)] = 0, [A1-D8, A5-D7] = 0.

The above new Definitions 19 and 21 introduce the extended GRACCF model

$$\sigma^{\text{SP-GMRACCF}}(T) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Q[i,j] \times T[i,j] + \left[\omega \times \sum_{k=0}^{n_c-1} C^{\text{cf}}[k,4] \times Q\left[C^{\text{cf}}[k,0], C^{\text{cf}}[k,1]\right] \times \overline{T}[k]\right] + \left[(1-\omega) \times \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} C^{\text{S}}[i,j] \times T[i,j]\right],$$

subject to Formulas (2)–(7), and

$$C^{\text{cf}}[k,4] = 0,\ 0 \leqslant k \leqslant n_c \text{ and } C^{\text{cf}}[k,4] < \tau_{\text{coop}} \tag{8}$$

$$C^{\text{cf}}[k,4] = 0,\ 0 \leqslant k \leqslant n_c \text{ and } C^{\text{cf}}[k,4] > \tau_{\text{conf}} \tag{9}$$

where $\sigma^{\text{SP-GMRACCF}}$ represents the group performance of the extended GMRACCF model based on semantic modification, and Formulas (8) and (9) cooperatively screen those automakers with high cooperation and low conflict potentials in the extended GMRACCF model.

With the above mentioned Definitions 19 and 21 and constraints, we propose the evaluation method. Here, we define additional symbols as follows to simplify our descriptions:

(1) "step" is a value that expresses the increasing step length of the automaker cooperatibn coefficient τ, and the range of step is $[0,1]$. In our scenario, we randomly set it to 0.05. Without loss of generality, we will carry out large-scale random experiments in Section 6.

(2) SP-GMRACCF ( ) is a function that extends the GMRACCF solution based on collaborative filtering and semantic modification.

This section proposes a method for evaluating semantic modifications based on collaborative filtering. The method aims to resolve conflicts in Q values and assist in identifying automakers with a high CCF value.

As shown in Figs. 2 and 3, applying semantic modification based on collaborative filtering results in a decrease in group performance σ as the cooperation coefficient increases. This indicates that stricter requirements for cooperation and conflict have a negative impact on the performance of CCF, although it still outperforms when considering only cooperation and conflict factors. However, administrators can effectively adjust whether a vehicle allocation strategy should be aggressive or conservative by simply adjusting the CCF threshold based on its current form. This section demonstrates that the semantics provide

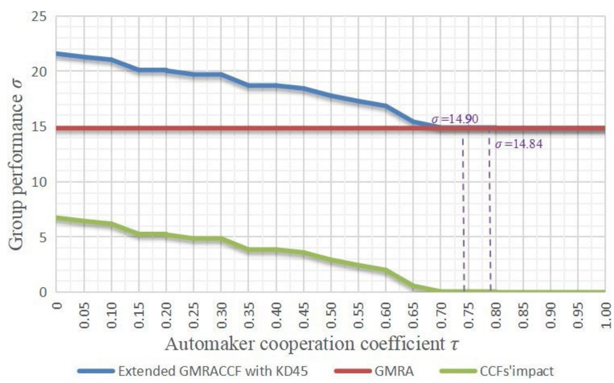

Fig. 3 Group performance with different τ values.

administrators with more suitable vehicle allocation policies and effectively ensure a minimum level of group performance.

5 Simulation

In order to verify the efficiency and robustness of our proposed method, we conduct a large-scale random simulation experiment on a configured computer. The experimental setup includes an Intel Core i5-12600K processor, 16.0 GB of memory, and the Windows 11 Pro operating system. We use PyCharm 2023.1 as the editor and Python 3 as the programming language.

In the simulation, we choose two different typical team sizes, namely ($m = 8$ and $n = 10$) and ($m = 16$ and $n = 22$), where m represents the number of automakers (agents) and n represents the number of city dealers (roles). These two sizes of automakers and city dealers correspond to the number of large automakers and vehicle dealers in first-tier cities that are well-known in the market, as well as the number of automakers with high sales in the country and car dealers in first-tier and second-tier cities. Since our proposed solution mainly involves predefined parameters $Q[i,j]$, $L[j]$, $L^a[i]$, ω, and τ, we run thousands of simulation experiments according to the range of these parameters in Table 5.

In addition, to simplify the description, we introduce the following symbols:

1) $C^{\text{cf}}_{\text{kd45}}$ represents the compact CCF matrix of $C^{\text{f}}_{\text{kd45}}$.

(2) T^{GMRACCF} represents matrix T obtained from the original GMRACCF model.

(3) $\overline{T}^{\text{GMRACCF}}$ is the CCF assignment result $\overline{T}$ obtained from the original GMRACCF model.

(4) $\sigma^{\text{SP-GMRACCF}}$ is the result of semantic modification performance, which is formalized as

$$\sigma^{\text{SP-GMRACCF}}(T) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Q[i,j] \times T^{\text{GMRACCF}}[i,j] + \left[\omega \times \sum C^{\text{cf}}_{\text{kd45}}[k,4] \times Q\left[C^{\text{cf}}_{\text{kd45}}[k,0], C^{\text{cf}}_{\text{kd45}}[k,1]\right] \times \overline{T}^{\text{GMRACCF}}[k]\right] + \left[(1-\omega) \times \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} C^{\text{S}}[i,j] \times T^{\text{GMRACCF}}[i,j]\right].$$

Table 5 Main parameters in simulation.

Parameter	Range or numerical value
$L[j]$	[1, 4]
$L^a[i]$	[1, 10]
ω	[0, 1]
τ	[0, 1]
$Q[i,j]$	[0, 1]

In order to validate the effectiveness of cooperative filtering and semantic modification, we conduct tests using both team sizes mentioned earlier.

Collaborative filtering primarily involves determining the weight coefficient ω for cooperation or conflict factors and the parameter step size. As it is a dynamic search for the optimal value of ω, we begin with the maximum value, i.e., $\omega = 1$. Figure 4 illustrates the variations in group performance with respect to asynchronous long values, demonstrates that in order to establish a more conservative (positive) sustainable vehicle allocation strategy, administrators must make a balanced trade-off by sacrificing the impact of cooperation scale (cooperation and conflict factors) appropriately.

Semantic modification mainly involves automobile manufacturer cooperation coefficient τ and parameter step size. Since the team evaluation method dynamically searches for the best value of τ, we start with the maximum value, that is, $\tau = 1$. Figure 5 illustrates the impact of asynchronous long values on group performance. The results show that when administrators aim to establish a sustainable conservative (positive) vehicle allocation strategy with a high CCFs impact, adjustments lead to a decrease (increase) in group performance of the vehicle sales chain.

We compare the group performance of the extended GMRACCF after collaborative filtering and semantic modification ($\sigma^{\text{SP-GMRACCF}}$), the extended GMRACCF after completion based on the KD45 algorithm (σ^{GMRACCF}(KD45)), and the original GMRACCF (σ^{GMRACCF}) under two different sizes. The simulation results are shown in Table 6, where λ_1 is defined as (σ^{GMRACCF}(KD45) $-$ σ^{GMRACCF})/σ^{GMRACCF}, and λ_2 is defined as ($\sigma^{\text{SP-GMRACCF}}$ $-$ σ^{GMRACCF}(KD45))/ σ^{GMRACCF}(KD45). Our findings indicate that in our vehicle allocation scenario, using the KD45 algorithm to complete the CCF matrix leads to an increase in group performance, but it is not consistently stable. On the other hand, the GMRACCF, through collaborative

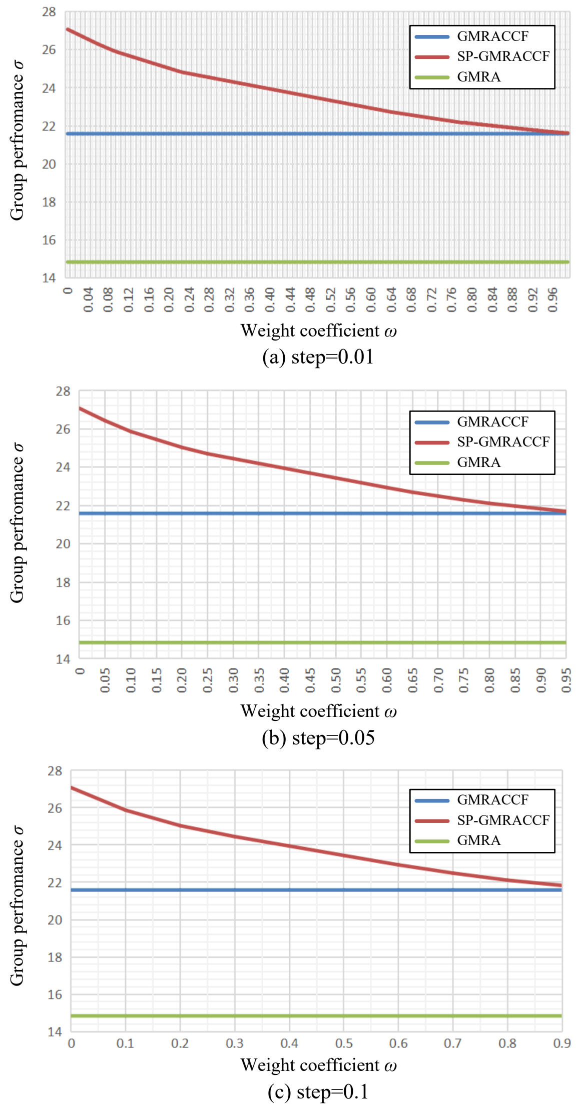

Fig. 4 Change in the group performance σ under different values of ω with different steps (m = 8, n = 10, 1 ⩽ L [j] < 4 (0 ⩽ j < 10), and 1 ⩽ L^a[i] < 10 (0 ⩽ i < 8)).

filtering and semantic modification, consistently ensures the improvement of group performance.

The average group performance comparison of the three models of two different sizes is illustrated in Fig. 6. Additionally, Fig. 7 provides evidence that our proposed collaborative filtering and semantic modification algorithm effectively enhances group performance. It is worth noting that the expanded GMRACCF model, which utilized the KD45 logic algorithm, took longer to find CCF influences compared to the original GMRACCF model, as demonstrated in Fig. 7.

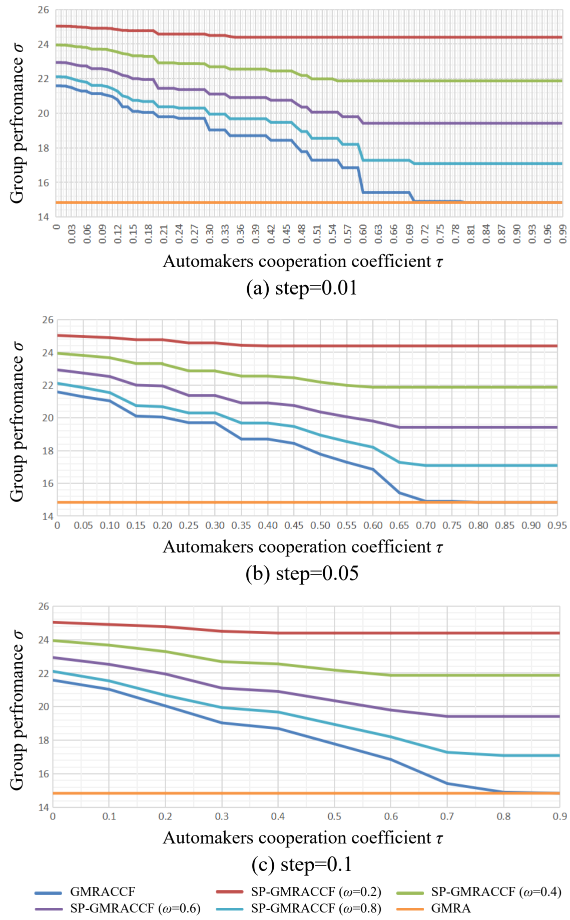

Fig. 5 Change in the group performance σ under different values of τ with different ssteps (m = 8, n = 10, 1 ⩽ L [j] < 4 (0 ⩽ j < 10), and 1 ⩽ L^a[i] < 10 (0 ⩽ i < 8)).

However, the time difference between the completed model with the KD45 algorithm and the model with collaborative filtering and semantic correction is not significant. However, when compared to the original model, the average vehicle allocation performance improved from 2.63% to 39.86%, which is a

Table 6 Simulation results from various models and different scales.

Scale	σ^{GMRACCF}	σ^{GMRACCF} (KD45)	$\sigma^{\text{SP-GMRACCF}}$	λ_1 (%)	λ_2 (%)
m = 8, n = 10	16.05	16.41	23.75	2.24	44.68
m = 10, n = 13	25.13	25.51	35.86	1.52	40.59
m = 12, n = 16	33.27	34.02	47.08	2.26	38.40
m = 14, n = 19	41.14	42.78	58.84	3.99	37.54
m = 16, n = 22	48.62	50.28	69.46	3.14	38.14

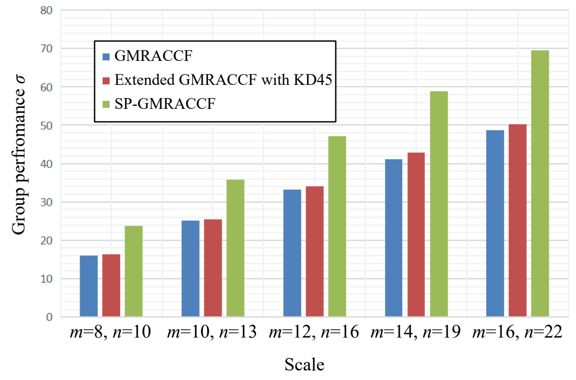

Fig. 6 Comparison of the average group performance σ.

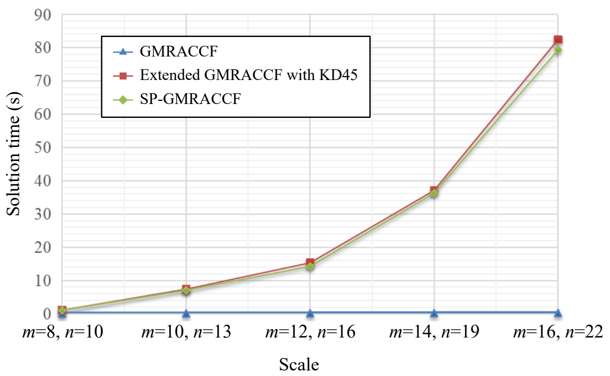

Fig. 7 Comparison solution time.

particularly significant improvement. Furthermore, the average time of the model with collaborative filtering and semantic modification is 3.81% shorter than that of the model completed by the KD45 algorithm, and the vehicle allocation strategy can be generated within two minutes.

From the above experiment, we can draw the following conclusions:

(1) Table 6 and Fig. 6 demonstrate the effectiveness of the KD45 logic algorithm in enhancing the overall performance of the sales chain through the identification of potential relationships among automakers.

(2) As shown in Fig. 4, when the weight coefficient ω of cooperation or conflict factors increases, it indicates that administrators' demands for vehicle allocation become increasingly strict.

(3) As shown in Fig. 5, the increase in the weight coefficient τ of cooperation or conflict factors leads to stricter requirements on the influence of CCFs, resulting in lower performance of CCFs. This corresponds to a more conservative allocation of vehicles by administrators.

(4) Figures 4–6 demonstrate that our proposed team evaluation method can effectively consider the influence of CS and CCFs. Additionally, it allows for setting the value of the cooperation or conflict factor weight coefficient to evaluate the group performance in relation to the individual performance of the automakers and the city dealer.

(5) As demonstrated in Fig. 8, adjusting the weight coefficient ω of cooperation and conflict can impact the vehicle allocation performance. Increasing (decreasing) these weights will result in lower (increased) performance. However, increasing (decreasing) the thresholds τ for cooperation and conflict can mitigate the negative impact on performance. This suggests that administrators have the ability to fine-tune the coefficients of the current strategy to achieve the desired vehicle allocation performance.

6 Related Work

The VAP is a resource allocation problem that has gained increasing attention. In recent years, many scholars have used various algorithms to study resource allocation problems.

Wei et al.[25] employed the Non-dominated Sorting Genetic Algorithm Ⅱ (NSGA -Ⅱ) to address the resource allocation problem in Vehicular Cloud Computing (VCC). However, this algorithm solely focuses on resource allocation and neglects real-time update information, making it unsuitable for vehicle allocation strategies that require real-time performance.

On the other hand, Luong et al.[26] utilized Deep Q-Learning (DQL) and Convex Difference Algorithm (DCA) to tackle the resource allocation problem in

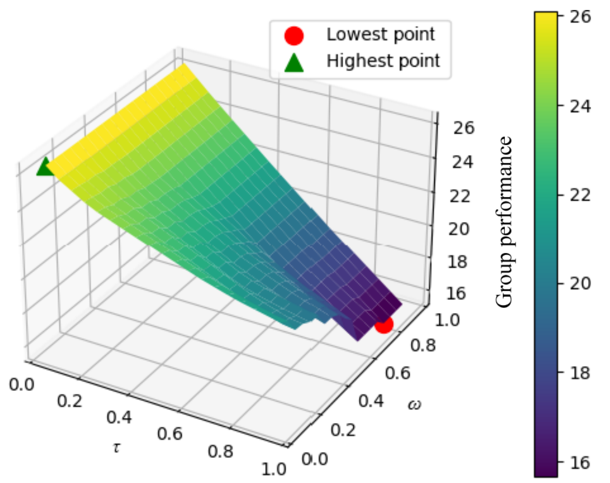

Fig. 8 Group performance with different τ values and different ω values.

Unmanned Aerial Vehicles (UAVs) cooperative wireless networks. However, the DQL algorithm only requires training the drone based on a smaller set of variables, such as the drone's location, rather than all the variables involved. In the context of automobile distribution, where all manufacturers and dealers need to be centralized for distribution, this approach is not applicable.

Many scholars have focused on solving the task allocation problem using the multi-agent system, also known as the agent-based method[27–30]. Some scholars have proposed a solution to the team establishment problem using RBC[31–33] and its basic GRA model[34–37]. This model is known for its centralized modeling and distributed execution[37]. Zhu et al.[1, 2] proposed a practical solution to the team management problem by formalizing the GRA+ algorithm, which essentially addresses a resource allocation problem. These findings suggest that RBC and E-CARGO are effective tools for formalizing and solving complex collaboration and management problems.

The previous studies demonstrate that RBC and its GRMA model have emerged as a practical unified model for addressing resource allocation problems.

In the VAP examined in this paper, there is a presence of commercial cooperation and competition among automakers. Merely utilizing the GMRA model is insufficient. To effectively implement GMRA, it is necessary to also take into account the CCF among automakers.

For example, Zhu et al.[9] proposed the GRACCF model, which considers both CCF and addresses the assignment of conflicting agents in optimization. Extensive simulation experiments demonstrate that GRACCF can assist administrators in forming high-performing teams by assigning employees, making it applicable to the vehicle allocation problem as well. However, previous methods have some limitations. Firstly, They used a questionnaire to construct the compact CCF matrix, which may not fully capture the potential relationship between automakers. To address this, Jiang et al.[22] developed the KD45 logic algorithm[23] to extend the GRACCF model and considered the potential relationship between automakers. However, Jiang et al.'s[22] algorithm overlooks the impact of cooperation scale on automakers and dealers in the vehicle allocation problem. The scale of cooperation not only affects the supply and demand between automobile manufacturers and dealers, but also influences factors such as price and inventory. In this study, we present an innovative approach called collaborative filtering with semantic modification. This approach offers valuable insights for administrators in formulating effective vehicle allocation strategies.

7 Conclusion

This paper proposes the extended GMRACCF model, which is based on collaborative filtering and semantic modification to establish a practical application of vehicle allocation.

In this paper, we first formalize the vehicle allocation problem through a simplified GMRACCF model. Then, we investigate the potential relationship between automakers and the cooperation scale between automakers and car city dealers, as it can impact the sustainability of vehicle allocation. To explore this relationship, we employ the KD45 logic algorithm. Additionally, we propose an evaluation method of collaborative filtering to assist administrators in determining the weight of cooperation and conflict, as well as the cooperation scale, on team performance based on specific requirements. Finally, we apply semantic modification to address conflict resolution of partial Q values, building upon the cooperative filtering approach.

The practicability and robustness of the proposed allocation method are demonstrated through an example. The simulation results provide a reliable reference for administrators to assess the overall performance of automakers and dealers based on dynamic demand and make informed decisions regarding vehicle allocation.

From this paper, further research on the extended GMRACCF model can be explored in the following directions.

(1) To obtain a compact CCF matrix between automakers, a more scientific and detailed index-based method can be employed.

(2) In order to evaluate the performance of the semantic modification algorithm in resolving Q-value conflicts, it is necessary to compare it with other machine learning algorithms.

(3) Finding Nash equilibrium with collaborative filtering and semantic modification.

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References

[1] H. Zhu, D. Liu, S. Zhang, Y. Zhu, L. Teng, and S. Teng, Solving the many to many assignment problem by improving the Kuhn-Munkres algorithm with backtracking, *Theor. Comput. Sci.*, vol. 618, pp. 30–41, 2016.

[2] H. Zhu, D. Liu, S. Zhang, S. Teng, and Y. Zhu, Solving the group multirole assignment problem by improving the ILOG approach, *IEEE Transactions on Systems, Man, and Cybernetics*: *Systems*, vol. 47, no. 12, pp. 3418–3424, 2017.

[3] H. Zhu, Avoiding conflicts by group role assignment, *IEEE Trans. Syst. Man Cybern, Syst.*, vol. 46, no. 4, pp. 535–547, 2016.

[4] X. Zhu, H. Zhu, D. Liu, and X. Zhou, Criteria making in role negotiation, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 50, no. 10, pp. 3731–3740, 2020.

[5] H. Zhu, Maximizing Group performance while minimizing budget, *IEEE Trans. Syst. Man Cybern, Syst.*, vol. 50, no. 2, pp. 633–645, 2020.

[6] H. Zhu, Avoiding critical members in a team by redundant assignment, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 50, no. 7, pp. 2729–2740, 2020.

[7] H. Zhu and M. Zhou, Role-based collaboration and its kernel mechanisms, *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.*, vol. 36, no. 4, pp. 578–589, 2006.

[8] H. Zhu, M. Zhou, and R. Alkins, Group role assignment via a Kuhn-Munkres algorithm-based solution, *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.*, vol. 42, no. 3, pp. 739–750, 2012.

[9] H. Zhu, Y. Sheng, X. Zhou, and Y. Zhu, Group role assignment with cooperation and conflict factors, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 48, no. 6, pp. 851–863, 2018.

[10] R. S. Kreitchmann, F. J. Abad, V. Ponsoda, M. D. Nieto, and D. Morillo, Controlling for response biases in self-report scales: Forced-choice vs. psychometric modeling of likertitems,*Front.Psychol.*,doi:10.3389/fpsyg.2019.02309.

[11] I. Ajzen, T. C. Brown, and F. Carvajal, Explaining the discrepancy between intentions and actions: The case of hypothetical bias in contingent valuation, *Pers. Soc. Psychol. Bull.*, vol. 30, no. 9, pp. 1108–1121, 2004.

[12] P. S. Brenner and J. DeLamater, Li es, damned lies, and survey self-reports? Identity as a cause of measurement bias, *Soc. Psychol. Q.*, vol. 79, no. 4, pp. 333–354, 2016.

[13] L. Fang, K. Wang, Z. Wang, and X. Wen, Disjunctive normal form for multi-agent modal logics based on logical separability, *Proc. AAAI Conf. Artif. Intell.*, vol. 33, no. 1, pp. 2817–2826, 2019.

[14] H. Zhu and R. Alkins, Group role assignment, in *Proc. Int. Symp. on Collaborative Technologies and Systems*, Baltimore, MD, USA, 2009, pp. 431–439.

[15] H. Zhu, M. Hou, and M. Zhou, Adaptive collaboration based on the E-CARGO model, *Int. J. Agent Technol. Syst.*, vol. 4, no. 1, pp. 59–76, 2012.

[16] H. Zhu and M. Zhou, Efficient role transfer based on Kuhn-Munkres algorithm, *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.*, vol. 42, no. 2, pp. 491–496, 2012.

[17] H. Zhu and M. Zhou, M-M role-transfer problems and their solutions, *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.*, vol. 39, no. 2, pp. 448–459, 2009.

[18] H. Zhu, Z. Yu, and Y. Gningue, Solving the exam scheduling problem with GRA, in *Proc. IEEE Int. Conf. Systems, Man, and Cybernetics* (*SMC*), Toronto, Canada, 2020, pp. 1485–1490.

[19] D. Liu, Y. Yuan, H. Zhu, S. Teng, and C. Huang, Balance preferences with performance in group role assignment, *IEEE Trans. Cybern.*, vol. 48, no. 6, pp. 1800–1813, 2018.

[20] H. Zhu, Social development paradox: An E-CARGO perspective on the formation of the Pareto 80/20 distribution, *IEEE Trans. Comput. Soc. Syst.*, vol. 9, no. 5, pp. 1297–1306, 2022.

[21] A. Schrijver, *Theory of Linear and Integer Programming*. Chichester, UK: Wiley, 1998.

[22] Q. Jiang, H. Zhu, Y. Qiao, D. Liu, and B. Huang, Extending Group role assignment with cooperation and conflict factors via KD45 logic, *IEEE Trans. Comput. Soc. Syst.*, vol. 10, no. 1, pp. 178–191, 2023.

[23] P. Blackburn, J. V. Benthem, and F. Wolter, Handbook of modal logic, https://shop.elsevier.com/books/handbook-of-modallogic/blackburn/978-0-444-51690-9, 2023.

[24] H. Wan, B. Fang, and Y. Liu, A general multi-agent epistemic planner based on higher-order belief change, *Artificial Intelligence*, vol. 301, p. 103562, 2021.

[25] W. Wei, R. Yang, H. Gu, W. Zhao, C. Chen, and S. Wan, Multi-objective optimization for resource allocation in vehicular cloud computing networks, *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 12, pp. 25536–25545, 2022.

[26] P. Luong, F. Gagnon, L. -N. Tran, and F. Labeau, Deep reinforcement learning-based resource allocation in cooperative UAV-assisted wireless networks, *IEEE Trans. Wirel. Commun.*, vol. 20, no. 11, pp. 7610–7625, 2021.

[27] M. Bristow, L. Fang, and K. W. Hipel, Agent-based modeling of competitive and cooperative behavior under conflict, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 44, no. 7, pp. 834–850, 2014.

[28] R. N. Almeida and N. David, Signs of heritage—An agent-based model of the dynamics of heritage categories, *IEEE Trans. Comput. Soc. Syst.*, vol. 6, no. 6, pp. 1283–1294, 2019.

[29] R. Mercuur, V. Dignum, and C. M. Jonker, Integrating social practice theory in agent-based models: A review of theories and agents, *IEEE Trans. Comput. Soc. Syst.*, vol. 7, no. 5, pp. 1131–1145, 2020.

[30] A. Trivedi and S. Rao, Agent-based modeling of emergency evacuations considering human panic behavior, *IEEE Trans. Comput. Soc. Syst.*, vol. 5, no. 1, pp. 277–288, 2018.

[31] B. Huang, H. Zhu, D. Liu, N. Wu, Y. Qiao, and Q. Jiang, Solving last-mile logistics problem in spatiotemporal crowdsourcing via role awareness with adaptive clustering, *IEEE Trans. Comput. Soc. Syst.*, vol. 8, no. 3, pp. 668–681, 2021.

[32] H. Zhu, Why did mr. trump oppose globalization? An E-CARGO approach, *IEEE Trans. Comput. Soc. Syst.*, vol. 8, no. 6, pp. 1333–1343, 2021.

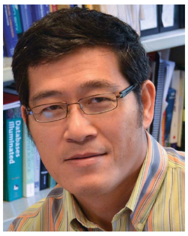
[33] D. Liu, B. Huang, and H. Zhu, Solving the tree-structured task allocation problem via group multirole assignment, *IEEE Trans. Autom. Sci. Eng.*, vol. 17, no. 1, pp. 41–55, 2020.

[34] Q. Jiang, H. Zhu, Y. Qiao, D. Liu, and B. Huang, Refugee resettlement by extending group multirole assignment, *IEEE Trans. Comput. Soc. Syst.*, vol. 10, no. 1, pp. 36–47, 2023.

[35] Q. Jiang, D. Liu, H. Zhu, Y. Qiao, and B. Huang, Quasi Group role assignment with role awareness in self-service spatiotemporal crowdsourcing, *IEEE Trans. Comput. Soc. Syst.*, vol. 9, no. 5, pp. 1456–1468, 2022.

[36] Q. Jiang, H. Zhu, Y. Qiao, Z. He, D. Liu, and B. Huang, Agent evaluation in deployment of multi-SUAVs for communication recovery, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 52, no. 11, pp. 6968–6982, 2022.

[37] D. Liu, Q. Jiang, H. Zhu, and B. Huang, Distributing UAVs as wireless repeaters in disaster relief via group role assignment, *Int. J. Coop. Info. Syst.*, vol. 29, no. 1n02, p. 2040002, 2020.



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