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How to Balance Dispatching, Transshipment, Distribution, and Reverse Logistics? A GMRA Approach for Agile Logistics

Ming Liao
School of Computer Science and Technology
Guangdong University of Technology
Guangzhou, China
840181769@qq.com

Hongze Guo
School of Computer Science and Technology
Guangdong University of Technology
Guangzhou, China
986277227@qq.com

Qian Jiang* (Corresponding Author)
School of Computer Science and Technology
Guangdong University of Technology
Guangzhou, China
qjiang@gdut.edu.cn

***Abstract*—In the highly competitive environment of modern logistics supply chains, achieving agility across the entire fulfillment lifecycle—specifically regarding dispatching (D), transshipment (T), distribution (D), and reverse (R) logistics—is a critical challenge. Unlike traditional scenarios where these operational stages are optimized in isolation, actual logistics processes exhibit interdependencies. Consequently, simple weighted evaluation methods fail to address the complex trade-offs required for comprehensive decision-making. To this end, we introduce the Multi-Factor Coupled Assignment (MFCA) model. Specifically, an extended Group Multi-Role Assignment (GMRA) model is integrated with an evolutionary algorithm: the coupled DTDR-related factors are adopted as the optimization variables, while the extended GMRA model serves to guide the evolutionary process, thereby enabling optimal task assignment under tightly entangled multi-stage constraints. Finally, simulation experiments are conducted to validate the effectiveness of the proposed method.**

***Keywords*—Role-Based Collaboration (RBC), Group Multi-Role Assignment (GMRA), Multi-Factor Coupling Assignment (MFCA).**

I. Introduction

In the era of smart logistics, the supply chain industry [1], [2] faces unprecedented pressure for agility. While enterprises often prioritize final delivery speed to secure immediate customer satisfaction, excessive focus on this single metric frequently disrupts other critical operations [3]. For instance, aggressive resource allocation to distribution (last-mile delivery [4]) often compromises Transshipment (inventory balancing) and Reverse Logistics (returns processing). Such imbalances erode supply chain resilience. Consequently, balancing multiple operational dimensions under finite resources (e.g., vehicle and sorting capacity) has become a fundamental requirement.

Effective resource allocation relies on matching tasks to the specific strengths of Logistics Service Providers (LSPs). However, traditional decision-making often evaluates LSPs based on aggregated historical performance, ignoring the heterogeneity of their capabilities across different stages. A node efficient in forward distribution may falter in complex reverse logistics. This limitation underscores the need for a more granular evaluation framework that recognizes the multi-stage nature of modern logistics tasks.

Crucially, the four dimensions of responsiveness—Dispatching, Transshipment, Distribution, and Reverse Logistics (DTDR)—are not isolated but tightly coupled through resource competition. For example, a surge in reverse logistics demand inevitably consumes sorting and transport capacities required for forward dispatching. Therefore, how to prioritize resource allocation by explicitly modeling these coupling relationships among DTDR factors remains a pivotal challenge in supply chain optimization.

Once all the demands have been specified, the core issue becomes how to perform the underlying many-to-many (M-M) assignment. From a modeling perspective, the multi-factor coupling assignment (MFCA) problem is essentially a M-M assignment problem. Role-Based Collaboration (RBC) [5], [6] and its Group Multi-Role Assignment (GMRA) model provide an effective framework for such assignments and have been widely used to solve M-M problems. However, the classical GMRA formulation does not explicitly capture the mutual coupling among DTDR. To address this limitation, this paper first develops the MFCA model as an extension of GMRA that embeds DTDR coupling into the assignment structure. Namely, we tightly integrate the extended GMRA with an evolutionary algorithm (EA), where the coupled DTDR factors serve as optimization variables and the extended GMRA model guides the evolutionary search.

The main contributions of this paper are summarized as follows: 1) We formulate the MFCA model specifically for the logistics supply chain. 2) To solve MFCA, we develop an extended GMRA–guided evolutionary algorithm that jointly optimizes coupled DTDR factors under tightly coupled multi-factor constraints. 3) Simulation experiments are conducted to demonstrate the practicality of the proposed solution.

The remainder of this paper is organized as follows. Section II introduces the real-world logistics scenario to illustrate the MFCA problem. Section III formally defines the problem via the extended GMRA model. Section IV describes the proposed algorithm for solving MFCA. Section V reports the simulation results and analyzes the feasibility and effectiveness of the solution compared to benchmarks. Section VI discusses related work. Finally, Section VII concludes the paper and outlines future research directions.

II. Real-World Scenario

To illustrate the MFCA problem, we introduce a scenario involving Company X, a major logistics service provider. In the

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previous fiscal year, Company X optimized operational metrics in isolation, aggressively prioritizing forward distribution speed. This strategy, however, neglected the coupled effects on other operational stages, causing severe bottlenecks in transshipment hubs and delays in returns processing.

To address this system-wide imbalance, Ann (CEO) initiated a comprehensive optimization project and delegated the resource allocation task to Bob (CTO). Recognizing that the root cause of past failures was the disregard for factor coupling, Bob proposed a new approach that explicitly accounts for the interactions among Dispatching, Transshipment, Distribution, and Reverse Logistics (DTDR).

First, Bob decomposed the logistics project into specific sub-tasks. The specific resource requirements (i.e., the number of logistics teams or units required) for each task are detailed in Table I.

TABLE I RESOURCE REQUIREMENTS FOR EACH LOGISTIC TASK

Task	$Task_1$	$Task_2$	$Task_3$	$Task_4$	$Task_5$	$Task_6$
Required LSPs	4	1	2	3	2	1

Subsequently, Bob investigated the operational bandwidth of each candidate LSP. He compiled a capacity constraint table detailing the maximum number of task units each LSP can simultaneously undertake without service degradation. The results are presented in Table II.

TABLE II SERVICE CAPACITY OF EACH CANDIDATE LSP

LSP ID	A	B	C	D	E	F	G	H	I	J	K	L
Capacity	3	2	6	4	5	5	3	4	7	5	6	1

Recognizing task allocation as a M-M problem with multi-factor coupling, Bob established four quantitative, time-based cost criteria where lower values denote superior performance: Dispatching (D_1), Quantified by Order Response Latency (ORL); Transshipment (D_2), assessed via Transshipment Dwell Time (TDT) at hubs; Distribution (D_3), quantified by Average Delivery Duration (ADD); and Reverse Logistics (D_4), defined by the Return Processing Cycle (RPC). Table III presents the normalized performance scores for D_1 (corresponding matrices for D_2-D_4 are omitted for brevity)

TABLE III NORMALIZED COST MATRIX FOR DISPATCHING (D_1)

LSP ID	Task				
	$Task_1$	$Task_2$	...	$Task_5$	$Task_6$
A	0.94	0.51	...	0.61	0.38
B	0.80	0.17	...	0.90	0.48
C	0.43	0.79	...	0.97	0.93
D	0.18	0.61	...	0.67	0.13
E	0.50	0.49	...	0.35	0.22
F	0.52	0.64	...	0.27	0.93
G	0.49	0.68	...	0.69	0.77
H	0.19	0.46	...	0.22	0.96
I	0.88	0.38	...	0.92	0.54
J	0.82	0.28	...	0.97	0.43
K	0.50	0.96	...	0.31	0.81
L	0.11	0.39	...	0.23	0.08

*Values in Table III range from 0 to 1, where 0 represents the lowest and 1 denotes the highest suitability. For display purposes, only the first and last two rows are shown.

By searching relevant literature, Bob learns that Role-Based Collaboration (RBC) and its GMRA model are effective for solving this kind of problem. Still, applying classic GMRA to this scenario faces two theoretical hurdles: the absence of a static qualification matrix due to dynamic resource contention, and the mathematical complexity of explicitly modeling the non-linear coupling among DTDR factors. To overcome these limitations, we propose an innovative extended GMRA solution detailed in the subsequent sections.

III. FORMALIZATIONS WITH EXTENDED GMRA MODEL

To formally address the MFCA problem within the logistics supply chain, we employ the GMRA framework as the foundational formalization method. We use nonnegative integers m (=$|\mathcal{A}|$, where $|\mathcal{A}|$ is the cardinality of set $\mathcal{A}$) to express the size of the agent set $\mathcal{A}$, n (= $|\mathcal{R}|$) the size of the role set $\mathcal{R}$, $i \in \{0, 1, \ldots, m-1\}$, and $j \in \{0, 1, \ldots, n-1\}$ the indices of agents and roles, respectively. To better describe the extended GMRA model, we introduce the following definitions.

Definition 1: A *role* [3], [4] is defined as r ::= <*id*, ®>, where *id* is the identification of r and ® is the set of requirements of properties for agents to play r.

Note: In the real-world scenario mentioned in Section II, roles are home appliance parts, with n equalling 6.

Definition 2: An *agent* [5], [6] is defined as a::= <*id*, $\mathbb{Q}$>, where *id* is the identification of a, $\mathbb{Q}$ is the set of a's values corresponding to the properties required in the group.

Note: In the scenario of Section II, agents are candidate LSPs. Namely, m = 12.

Definition 3: *Ability limit vector* L^a [7] is an m-vector, where $L^a[i]$ represents the upper limit of agent i's abilities.

Note: L^a represents the maximum number of concurrent task units that agent i can undertake. With respect to Table II, the L^a of the real-world scenario is [3, 2, 6, 4, 5, 5, 3, 4, 7, 5, 6, 1].

Definition 4: *Role range vector* L [8] is an n-dimensional vector, which represents the number of agents required for roles, i.e., $L[j] \in \{1, 2, \ldots, m\}$ $(0 \leq j < n)$.

Note: In the context of Section II, a role corresponds to a specific logistics operation (e.g., Dispatching or Distribution) that necessitates the collaboration of multiple LSPs to meet the operational volume. Namely, L = [4, 1, 2, 3, 2, 1].

Definition 5: A *threshold matrix* γ [9] is an $m \times n$ matrix. It satisfies the equation that $\gamma[i, j] = min\{L[j], L^a[i]\}$. This equation represents that $\gamma[i, j]$ is the maximum value for the control variable $T[i, j]$ to take.

Definition 6: A *Qualification matrix* Q [10] is an $m \times n$ matrix, where $Q[i, j] \in [0, 1]$ expresses the qualification value of agent i $(0 \leq i < m)$ for role j $(0 \leq j < n)$. $Q[i, j] = 0$ 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 the classic RBC framework, Q is typically a static input. However, in the context of MFCA, the final Q matrix is not pre-determined. It is the complex result of coupling the four DTDR factors. Generating this coupled Q matrix is the central focus of our method. Therefore, we proposed the following original definitions to solve the tackles above.

Definition 7: To capture the multi-dimensional nature of logistics, we define four specific qualification matrices $Q_l \in [0, 1]^{m\times n}$, corresponding to the four DTDR dimensions ($l \in \{D_1, D_2, D_3, D_4\}$).

Note: Since the metrics defined in Section II (ORL, TDT, ADD, RPC) are time-based costs (where lower is better), the entries in Q_l are obtained by normalizing and inverting the raw data (i.e., mapping the minimum time cost to a qualification of 1). The specific correspondences are: Q_{D1} (Dispatching): Derived from Order Response Latency. Q_{D2} (Transshipment): Derived from Transshipment Dwell Time. Q_{D3} (Distribution): Derived from Average Delivery Duration. Q_{D4} (Reverse Logistics): Derived from the Return Processing Cycle.

Definition 8: A *DTDR weight vector W* denote the weight vector associated with Dispatching, Transshipment, Distribution, and Reverse Logistics, respectively. Here, $W = [w_{D1}, w_{D2}, w_{D3}, w_{D4}]$, $W[k] \in (0, 1]$ ($k \in \{0, 1, 2, 3\}$).

Note: The weights reflect the decision-maker's strategic preferences. A larger w_{D1} prioritizes rapid Dispatching (minimizing order latency). A larger w_{D2} emphasizes Transshipment efficiency (reducing hub dwell time). A larger w_{D3} focuses on Distribution speed (last-mile delivery). A larger w_{D4} prioritizes Reverse Logistics (handling returns). Since resources are finite, all four operational dimensions are essential; thus, they are assigned strictly positive weights.

Definition 9: A *minimum weight threshold* w_{min} denotes the minimum allowable weight for any component of vector *W*. Namely, $W[k] \geq w_{min}$ $(0 \leq k < 4)$.

Note: In the logistics scenario, w_{min} represents the baseline operational requirement. Assigning a weight below this threshold implies a neglect of a critical supply chain stage, which is impermissible. We randomly set $w_{min} = 0.01$ to ensure basic functionality across all stages.

Definition 10: Let $f_w, g_w : (0, 1]\rightarrow[0, +\infty)$, and $k_w: [0, +\infty) \rightarrow [0, +\infty)$ be three scalar mapping functions. Given a primary Dispatching weight $w_{D1} \in (0, 1]$, the functional DTDR weight vector $\widetilde{W}$ is defined as $\widetilde{W}(w_{D1}) = [w_{D1}, f_w(w_{D1}), g_w(w_{D1}), k_w(f_w(w_{D1}))]$.

Note: These functions model the intrinsic coupling of DTDR: f_w captures the dependency between Dispatching and Transshipment; g_w links Dispatching with Distribution; and k_w models the trade-off between Transshipment and Reverse Logistics. Thus, the four weights are not independent but entangled.

While these functional dependencies are typically derived in practice by regressing historical data from the four qualification matrices (i.e., Q_l), we randomly instantiate specific synthetic relations here to validate algorithmic robustness: Transshipment is modeled as $w_{D2} = f_w(w_{D1}) = 0.2 + 0.6\,w_{D1}{}^{1.2}$ (convex increasing), reflecting that higher dispatching speeds demand stronger transshipment support. Subsequently, Reverse Logistics follows a linear decrease $w_{D4} = k_w(f_w(w_{D1})) = 0.6-0.5w_{D2} = 0.6-0.5\times(0.2 + 0.6w_{D1}{}^{1.2})$, simulating resource competition where excessive forward transshipment reduces reverse capacity. Finally, Distribution is defined as an inverted-U function $w_{D3} = 0.3 + 0.4\times[1-(2w_{D1}-1)^2]$, which peaks at $w_{D1} = 0.5$, indicating that distribution receives maximum emphasis under moderate dispatching pressure.

It is crucial to note that the specific formulas presented above serve primarily for the case study; in the large-scale experiments, the functional relationships themselves (i.e., the coefficients and trend types of f_w, g_w, k_w) are stochastically generated to verify the algorithm's generalizability under diverse coupling scenarios.

Definition 11: Given a vector $\widetilde{W}(w_{D1})$, the *projected DTDR weight vector* $W(w_{D1}) = \Pi_{w_{min}}(\widetilde{W}(w_{D1}))$, where $\Pi_{w_{min}}: \mathbb{R}^4\rightarrow\Delta_{w_{min}}$ is a projection operator that maps any raw vector onto $\Delta_{w_{min}}$, and $\Delta_{w_{min}} = \{W \in \mathbb{R}^4 \mid \sum_0^3 W[k] = 1, W[k] \geq w_{min}, 0 \leq k < 4\}$.

Note: In implementation, $\Pi_{w_{min}}$ is realized as a projection with a lower bound, which enforces the minimum-weight constraint $W[k] \geq w_{min}$ for all k. In addition, we impose the unit-sum condition $\sum_0^3 W[k] = 1$ as a normalization convention to facilitate a fair comparison with existing GMRA-based algorithms, rather than as an intrinsic requirement of the proposed method.

Definition 12: An *aggregated DTDR qualification matrix* $\widetilde{Q}$ is an $m\times n$ matrix, where $\widetilde{Q}(w_{D1}) \in [0, 1]^{m\times n}$, and $\widetilde{Q}[i, j] = w_{D1}Q_{D1}[i, j] + w_{D2}Q_{D2}[i, j] + w_{D3}Q_{D3}[i, j] + w_{D4}Q_{D4}[i, j]$.

Note: Once Q_{D1}, Q_{D2}, Q_{D3}, Q_{D4}, and $W(w_{D1})$ are determined, $\widetilde{Q}$ is uniquely defined.

Definition 13: *Role assignment matrix T* [9] is defined as an $m \times n$ matrix, where $T[i,j] \in \mathbb{N}$ $(0 \leq i < m, 0 \leq j < n)$ expresses how many workload units of agent *i* are assigned to role *j* or not.

Definition 14: *Group performance* σ [11] is defined as the sum of the assigned agents' qualifications, and the formula is as follows:

$$\sigma = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} Q[i, j] \times T[i, j].$$

Note: The physical meaning of σ is the objective function.

Definition 15: Role *j* is *workable* [12] in group *g* if it has been assigned to sufficient agent capacity

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

Note: Role *j* is *workable* means that there are enough teams to fulfill the workload units for all requirements of product *j*.

Definition 16: *T* is *workable* [13][14] if each role *j* is *workable*, and group *g* is *workable* if *T* is *workable*.

Definition 17: Given $\widetilde{Q}$, L, L^a, γ, The MFCA model is to find a *workable T* to obtain:

$$min\ \sigma_{MFCA} = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} \widetilde{Q}[i, j] \times T[i, j], \quad (1)$$

Subject to

$$0 \leq T[i, j] \leq \gamma[i, j]\ (0 \leq i < m, 0 \leq j < n), \quad (2)$$

$$\sum_{i=0}^{m-1} T[i, j] = L[j]\ (0 \leq j < n), \quad (3)$$

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

where Expression (3) depicts that all the requirements can be accomplished by enough teams, and Expression (4) indicates that all agents will not undertake roles that exceed their ability.

Definition 18: Let $w_{D1} = w_{D2} = w_{D3} = w_{D4} = 0.25$. Under this condition, given $\widetilde{Q}$, L, L^a, γ, the weighted GMRA (WGMRA) model [9] is to find a workable T to obtain $min\ \sigma_{WGMRA} = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} \widetilde{Q}[i,j] \times T[i,j]$ subject to (2)-(4).

Note: WGMRA represents an assignment strategy where all weights are considered equally important; it serves as the comparative baseline in this paper.

From Definition 17, the key part for solving MFCA requires specifying the vector W. However, because the DTDR dimensions are tightly intertwined, it is not straightforward to assign reasonable values to these weights. Existing GMRA-based extended models usually assume that group performance is known in advance, and then solve the model under that assumption, which does not fit our case properly.

IV. MFCA ALGORITHM

As mentioned in Section III, the main challenge is how to qualify matrix $\widetilde{Q}$ through projected DTDR weight vector $W(w_{D1})$ before solving MFCA. Here we take a different route. Once $W(w_{D1})$ is fixed, the objective function of MFCA (i.e., Equation (1)) is uniquely determined. That is, the core of the problem is to search for an appropriate W. Based on this observation, we deeply integrate the MFCA model with an EA and design an optimization procedure tailored to MFCA. Concretely, we treat W as the decision variable and use σ_{MFCA} as the fitness function guiding the evolution process. This obtains a practical solving strategy for MFCA. The overall algorithmic workflow is summarized in the pseudocode of Algorithm 1.

As formulated in Section III, the central challenge in solving the MFCA problem lies in determining the aggregated DTDR qualification matrix $\widetilde{Q}$, which is intrinsically derived from the functional DTDR weight vector $\widetilde{W}$. Since the coupling relationships are non-linear, deriving $\widetilde{Q}$ analytically is intractable.

Here, we adopt a nested optimization strategy. We observe that once the primary dispatching weight w_{D1} is fixed, the initial entire weight vector W' is uniquely determined via the coupling functions (Definition 10), which in turn determines the objective function of the assignment model. Consequently, the core problem transforms into searching for the optimal W that minimizes the total system cost.

Based on this observation, we deeply integrate the extended GMRA model with an EA. Specifically, we treat W as the decision variable for the evolutionary search, while the group performance σ_{MFCA} serves as the fitness function. This creates a bi-level structure: the EA explores the parameter space of coupling configurations, and for each candidate configuration, the extended GMRA solves the specific assignment sub-problem. The overall workflow is formalized in Algorithm 1.

Algorithm 1: MFCA Algorithm

Input: $\mathbf{Q} = \{Q_{D1}, Q_{D2}, Q_{D3}, Q_{D4}\}$, $\widetilde{W}$, L, L^a, γ, Iterative count for EA (*gens*)
Output: T^*, W^*
begin
Initialization: $\mathbf{P} \leftarrow$ Generate random weight vectors based on $\widetilde{W}$.
For $g = 1$ to *gens* do:
  For each individual $W \in \mathbf{P}$ do:
    Update $\widetilde{Q}$ via W and $\mathbf{Q}$
    // Solving the MFCA model via CPLEX
    $(T', \sigma') \leftarrow$ SOLVE_MFCA($\widetilde{Q}, L, L^a, \gamma$)
    Penalty $\leftarrow$ Calculate unmet demands in T' against L
    Fitness $\leftarrow \sigma' +$ *Penalty*
    Utilize *Fitness* to update global best T^*, W^*
  End For
  $P_{new} \leftarrow$ Apply Elitism, Tournament Selection, Crossover, Mutation
  $\mathbf{P} \leftarrow P_{new}$
End For
return T^*, W^*

Algorithm 1 highlights a critical procedure: once a candidate weight vector W is generated by the EA, it is fed into the extended GMRA model to construct the matrix $\widetilde{Q}$, which is then solved to optimality of this model using the CPLEX solver.

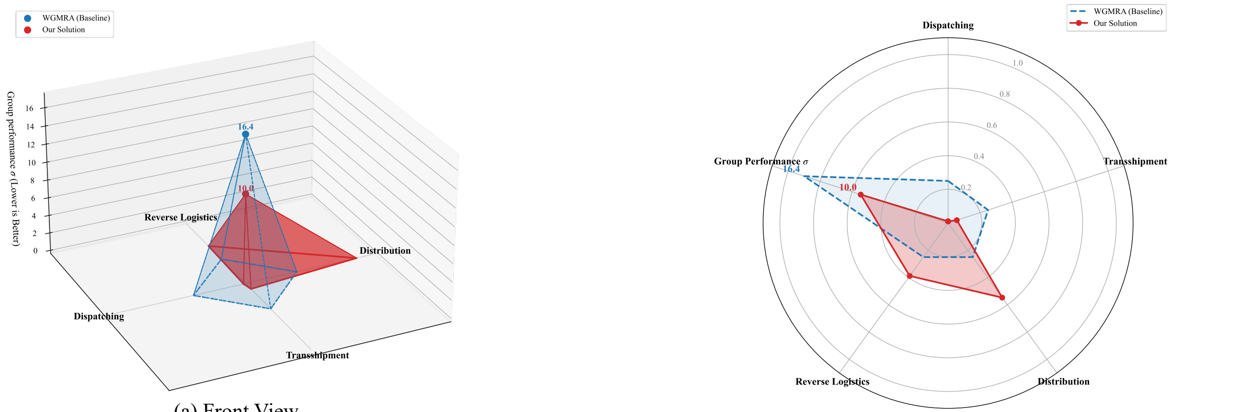
To valid the efficacy of this approach, we applied Algorithm 1 to the real-world logistics scenario described in Section II. The proposed MFCA method achieved a total system cost of $\sigma_{MFCA} = 3.64$, with the optimized DTDR weight vector converging to $W_{MFCA} = [0.46, 0.38, 0.03, 0.13]$. In stark contrast, applying the benchmark WGMRA to the same scenario—which ignores coupling and assumes a fixed equal-weight yielded a significantly higher cost of $\sigma_{WGMRA} = 4.39$.

This comparison confirms that the proposed method not only outperforms WGMRA by reducing the total time-cost by approximately 17%, but also validates its capability to dynamically adapt to the complex coupling constraints among DTDR factors. This makes MFCA a far more viable solution for practical, resource-constrained logistics decision-making.

V. SIMULATION AND EXPERIMENT

A. Configuration

To verify the feasibility and validity of the methods presented in this paper, we conducted experiments with random groups based on different scales of role numbers. First, we built our experimental platform on a desktop computer equipped with an AMD Ryzen 7 8845H CPU and 16 GB of RAM to run the



(a) Front View

(b) Top View

Fig.1. Comparative analysis of the group performance under DTDR. Note: The pyramid height in (a) denotes the group performance σ, where a lower value indicates better performance.

simulations. The code was developed in PyCharm using Python 3.6. Moreover, the parameters used in our experiments are listed in Table IV. Based on historical data from the industrial chain, we set their ranges as follows.

TABLE IV RANGES OF VITAL PARAMETERS

Parameter	Definition	Range or Value
m	Number of agents	{10, 20, 30, …, 100}
n	Number of roles	{5, 10, 15, 20, 25}
$L[j]$	Number of agents required for role j	{1, 2, 3, 4, 5}
$L^a[i]$	agent i's capacity for playing roles	{1, 2, 3, 4, 5}
pop	Population size	60
gens	Iteration count	120
p_c	Crossover probability	0.9
p_m	Mutation probability	0.2

B. Experiment

All simulation experiments were conducted using the parameter specifications listed in Table IV. To intuitively demonstrate the impact of coupling-aware optimization, Fig. 1 provides a two-view visualization of the weighting results for the four operational dimensions—Dispatching, Transshipment, Distribution, and Reverse Logistics.

In Fig. 1(a), the X–Y plane depicts the radial layout of the four DTDR weights, while the Z-axis denotes the resulting total system cost (σ), where a lower value indicates superior performance. The red pyramid represents the optimal weight configuration and minimal cost achieved by the proposed MFCA, whereas the blue dashed pyramid corresponds to the baseline WGMRA method (equal weights). Fig. 1(b) presents the corresponding top-down view, highlighting the distinct divergence in weight distribution between the two strategies.

From these visual comparisons, it is evident that the MFCA-derived solution locates a significantly lower cost valley compared to the baseline. This confirms that by explicitly modeling the coupled constraints, MFCA identifies a specific, non-trivial weight configuration W_{MFCA} that outperforms the rigid equal-weight assumption of WGMRA.

To evaluate the computational efficiency and scalability of the proposed method, we examined its solving time across varying problem dimensions. As illustrated in Fig. 2, we progressively increased the cardinality of the role set (n) and agent set (m) and recorded the execution time for each instance. The trend indicates that the algorithm's running time grows loosely polynomially rather than exponentially. This demonstrates that the extended GMRA-guided evolutionary search remains computationally tractable and can yield optimal solutions within an acceptable timeframe, even for medium-to-large-scale logistics networks.

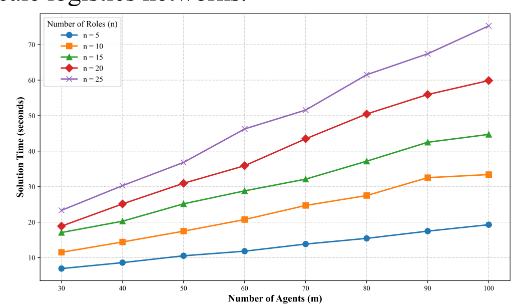


Fig. 2. Solution time for the proposed method at different scales.

The experimental results show that the proposed method produces a markedly lower group performance and a more reliable weight distribution compared with the GMRA-related method. These findings indicate that the proposed approach effectively captures decision-makers' preferences and translates them into superior task-allocation outcomes. Moreover, the generality of the MFCA formulation suggests broad applicability to domains with multi-factor trade-offs, such as automotive supply-chain coordination, humanitarian resource allocation, and refugee resettlement. Thus, extending MFCA offers a promising decision-support paradigm for complex, preference-driven allocation scenarios.

VI. RELATED WORK

A. Research on Logistics Resource Allocation and Supply Chain Agility

In the context of Industry 5.0 and smart logistics, research has demonstrated that the effective orchestration of LSPs and operational tasks is crucial for achieving supply chain resilience and service agility [1], [15]–[17]. Unlike traditional linear supply chains, modern logistics networks require a dynamic balance between forward execution (i.e., dispatching and distribution) and backward flows (i.e., reverse logistics). In this environment, the combination of robust resource scheduling and diversified capability provisioning has become a key path for enterprises to seek competitive advantages. Consequently, the introduction of the M-M assignment model provides a novel perspective for optimizing logistics resource allocation and enhancing comprehensive response capabilities [19]–[22].

Recent studies heavily prioritize integrated network design. For instance, Tirkolaee *et al.* [15] proposed a multi-objective framework to balance operational costs with environmental and reliability constraints under uncertainty. Expanding this scope, Ghatreh Samani and Hosseini-Motlagh [16] focused on Closed-Loop Supply Chains (CLSC), demonstrating that the joint optimization of forward and reverse flows is essential to avoid suboptimality caused by ignored coupling. Furthermore, Ivanov [17] introduced the concept of "viability," arguing that allocation strategies must explicitly reconcile the trade-off between efficiency and redundancy to ensure resilience against systemic disruptions.

B. RBC and GMRA

The theory of RBC has evolved from industrial automation to complex autonomous systems [4], [5], [23]. At its core, the E-CARGO (Environments, Classes, Agents, Roles, Groups, and Objects) meta-model [5] effectively formalizes such problems, as demonstrated by Zhu's analysis of global capital investment [10] and Jiang *et al.*'s extended GMRA for refugee resettlement involving stability feedback [9]. These applications establish GMRA as a powerful tool for M-M assignment problems [23].

However, existing GMRA approaches typically assume a predetermined qualification matrix Q. Addressing this limitation, this paper introduces a novel qualification synthesis method to solve the MFCA problem.

VII. Conclusion

To address the limitations of isolated metric optimization in modern logistics supply chains, this paper proposes the MFCA model. By explicitly characterizing the complex coupling relationships and resource competition among DTDR, we developed an extended GMRA-guided evolutionary algorithm. This approach transforms the intractable multi-stage resource allocation problem into a tractable optimization task. Validation through a logistics case study demonstrates that integrating factor coupling into the assignment structure significantly reduces the total system cost compared to traditional isolated evaluation methods, offering a robust solution for enterprises facing strict resource constraints.

Future work will focus on two main aspects: 1) incorporating data-driven techniques (e.g., deep reinforcement learning) to enable real-time adaptation of coupling coefficients in highly dynamic, stochastic environments; and 2) extending the applicability of the proposed framework to other domains with conflicting objectives, such as emergency disaster relief coordination or cross-border multimodal transport networks.

References

[1] N. Zarbakhshnia, Y. Wu, K. Govindan, and H. Soleimani, "A novel hybrid multiple attribute decision-making approach for outsourcing sustainable reverse logistics," *J. Clean. Prod.*, vol. 242, p. 118461, 2020.

[2] K. J. Cha and Y. S. Kim, "Critical success factors for mutual collaboration with suppliers in IT outsourcing industry: a case study of a top IT outsourcing company in Korea," *Enterp. Inf. Syst.*, vol. 12, no. 1, pp. 76–95, 2018.

[3] Q. Jiang et al., "Iterative Role Negotiation via the Bilevel GRA++ With Decision Tolerance," *IEEE Trans. Comput. Soc. Syst.*, vol. 11, no. 6, pp. 7484–7499, 2024.

[4] 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.

[5] H. Zhu, "Role-Based Collaboration and E-CARGO: Revisiting the Developments of the Last Decade", *IEEE Syst., Man, Cybern. Mag.*, vol. 1, no. 3, July 2015, pp. 27-35.

[6] W. Chen, Y. Tang, H. Zhu, and D. Liu, "ERAP optimization via en hanced constraints and boundary detection in GMRA," *IEEE Trans. Serv. Comput.*, early access, Oct. 10, 2025, doi: 10.1109/TSC.2025. 3620092.

[7] Q. Jiang, D. Liu, H. Zhu, B. Huang, N. Wu and Y. Qiao, "Group Role Assignment With Minimized Agent Conflicts,"*IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 55, no. 3, pp. 1844-1857, 2025.

[8] 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.

[9] 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.

[10] 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.

[11] Q. Jiang, D. Liu, H. Zhu, Y. Qiao, and B. Huang, "Equilibrium Means Equity? An E-CARGO Perspective on the Golden Mean Principle," *IEEE Trans. Comput. Soc. Syst.*, vol. 10, no. 4, pp. 1443–1454, 2023.

[12] H. Zhu, "Group Role Assignment with Constraints (GRA+): A New Category of Assignment Problems, " *IEEE Trans. Syst. Man, Cybern. Syst.,* vol. 53, no. 3, Mar. 2023, pp. 1670-1683.

[13] H. Zhu, "Pareto Improvement: A GRA Perspective," *IEEE Trans. Comput. Soc. Syst.,* vol. 10, no. 3, 2023, pp. 1241-1251.

[14] 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, 2022, pp. 1297-1306.

[15] B. Tirkolaee, S. Sadeghi, F. E. Moosavi, and H. K. Vandchali, "Ap plication of Robust Optimization for Green Supply Chain Network Design: A Case Study of Automotive Industry," *Comput. Ind. Eng.*, vol. 157, p. 107318, 2021.

[16] M. R. Ghatreh Samani and S. M. Hosseini-Motlagh, "A distinct robust programming for a closed-loop supply chain network design under hybrid uncertainty, " *Comput. Ind. Eng.*, vol. 159, p. 107519, 2021.

[17] D. Ivanov, "Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic," *Ann. Oper. Res.*, vol. 319, no. 1, pp. 1411–1431, 2022.

[18] M. Pellicelli, "Gaining flexibility and innovation through offshore outsourcing," *Sustain.*, vol. 10, no. 5, 2018.

[19] L. Ensslin, C. C. Mussi, A. Dutra, S. R. Ensslin, and S. N. Demetrio, "Management support model for information technology outsourcing," *J. Glob. Inf. Manag.*, vol. 28, no. 3, pp. 123–147, 2020.

[20] S. Lahiri, A. Karna, S. Chittaranjan Kalubandi, and S. Edacherian, "Performance implications of outsourcing: A meta-analysis," *J. Bus. Res.*, vol. 139, pp. 1303–1316, 2022.

[21] C. P. Garg and A. Sharma, "Sustainable outsourcing partner selection and evaluation using an integrated BWM–VIKOR framework," *Environ. Dev. Sustain.*, vol. 22, no. 2, pp. 1529–1557, 2020.

[22] P. Ji, H. Y. Zhang, and J. Q. Wang, "Selecting an outsourcing provider based on the combined MABAC–ELECTRE method using single-valued neutrosophic linguistic sets," *Comput. Ind. Eng.*, vol. 120, pp. 429–441, 2018.

[23] H. Zhu, *E-CARGO and Role-Based Collaboration: Modeling and Solving Problems in the Complex World*. USA: Wiley-IEEE Press, 2022.