Cooperative Package Assignment for Heterogeneous Express Stations

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***Abstract*—The success of online shopping accelerates the development of express delivery business with economic and efficient service. Current express delivery systems usually deliver the packages in noncooperation mode and cannot jointly optimize the express fee and moving cost of users. This paper proposes the cooperative package assignment system by lumping packages at the same express station to share the express fee, and proposes a novel pricing structure to stimulate the express stations to join the system without revenue loss by introducing cooperation cost. We formulate the *cooperative package assignment (CPA)* problem with heterogeneous express stations for joint optimization of users' express fee and moving cost. Then, an approximate algorithm, *CPAA*, is proposed for the *CPA* problem based on the greedy approach using submodular function minimization. We show that the designed algorithm achieves computational efficiency and guaranteed approximation. Furthermore, we model the large-scale *CPA* problem as *CPA-game* and present a game theoretic algorithm, *CPAGA*. We show that *CPA-game* has at least one *Nash Equilibrium*, and *CPAGA* finally converges to a pure *Nash Equilibrium*. Through extensive simulations, we demonstrate that *CPAA* and *CPAGA* show great advantages in terms of comprehensive cost, which is 28.1% and 19.9% lower than that in noncooperation mode on average, respectively. Moreover, *CPAGA* shows great scalability and is more suitable for large-scale cooperative package assignment systems.**

***Index Terms*—cooperative package assignment, express station, coalition formation game, submodular function**

I. Introduction

ONLINE purchasing has been evolving the retailing market, and has become the primary shopping mode with the rapid development of Internet and mobile networks. The statistical results from the State Post Bureau show that the business of express delivery involves 63.52 billion deliveries of goods in 2019, with average growth rate of 35.86% over the past five years in China [1]. During the online shopping festival of China in 2019, the delivery amount exceeded 1.29 billion [2]. The success of online shopping accelerates the development of express delivery business. There is an ever-increasing requirement for punctuality, economy and efficiency of express delivery service.

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TABLE I
PRICING RULES OF EXPRESS COMPANIES FOR LOCAL PACKAGES.

Company \ Price	First Heavy (1kg)	Continued Heavy (0.5kg)
FedEx	CNY 16	CNY 1
SF-Express	CNY 12	CNY 1
EMS	CNY 12	CNY 1
Deppon	CNY 10	CNY 1

In an express delivery network, the package is firstly delivered to the express station (ES) nearby, then forwarded to another ES close to the destination, and finally sent to the customer. Traditionally, the express package sender always delivers the package to the ES close to its current location non-cooperatively. However, the users can benefit from cooperative package assignment at the same ES by sharing the cost. Table I shows the pricing rules of express companies for local packages. The users can obtain cooperative surplus by lumping packages into one big package at express station. Specifically, the small packages can benefit through sharing the first heavy price, and the big packages can benefit from the cooperation since the continued heavy price is much lower than the first heavy price in practice.

With the fast development of sharing economy, the cooperative pricing mechanism design has been widely studied in various fields, such as blockchain [3], crowdsensing [4] and wireless charging [5]. Recently, some cooperative pricing mechanisms for logistics or express delivery have been proposed. *Wang et al.* proposed the cooperative operation of the express enterprise service network to optimize the operation efficiency of the stock resources [6]. *Yao et al.* studied the assessment of collaboration in city logistics by taking into account the transportation cost [7]. *Liu et al.* proposed a cooperative pricing model to achieve the final balanced price of both market and express companies [8]. *Ko et al.* proposed a pricing model based on last mile delivery time function to maximize the profit [9]. In [10], Shapley value was applied to give fair allocation to each company based on its marginal contribution. *Hong et al.* proposed a cost sharing model of terminal joint distribution for express enterprises to reduce delivery cost [11].

The collaboration or strategic alliance in express delivery services has also been widely studied. The realistic collaboration model that reduced the price of deliveries by creating an efficient pick-up and delivery system through a strategic alliance was proposed in [12]. *Kim et al.* developed a heuristic algorithm based on genetic algorithm to solve

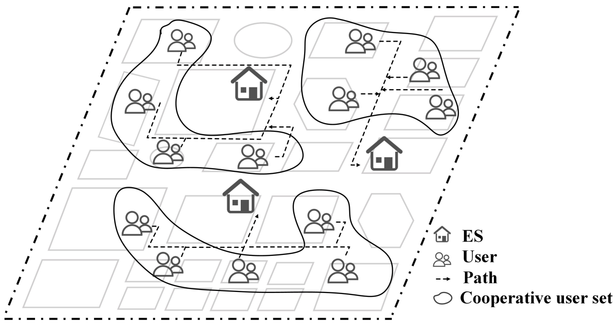


Fig. 1. Illustration of cooperative package assignment system.

the collaboration-based pick-up and delivery problem with the objective of maximizing the incremental profits of allied companies [13]. *Ferdinand et al.* suggested two types of strategic alliance models to improve efficiency of resource usages in a distribution system of goods [14]. *Dahl et al.* illustrated that cost effectiveness can be improved substantially through the suitable distributed decision support system in small transportation firm cooperation network [15].

However, most research on express delivery mainly focused on transportation between distribution centers. None of these studies considered the cooperative package assignment at ESs and the cost sharing among the cooperative packages. Furthermore, most researchers did not take into account the joint optimization of express fee and moving cost of users.

As shown in Fig. 1, we consider a cooperative package assignment system, where each user has several choices to deliver its package to different ESs, and each choice is with a corresponding moving cost. We consider that the ESs are heterogeneous, that is, the ESs are operated by different express companies with different prices. The users who deliver the packages at the same ES can obtain the cooperative surplus through sharing the total cost of users assigned to the ES.

Obviously, the cooperative package assignment system brings the economic benefit to the users, thus is very attractive to users. If the current pricing rule can guarantee the revenue of express companies, such system helps to attract more users without revenue loss. From the perspective of social competition, the cooperative package assignment system provides a novel pricing structure of ESs and prompts the express company to decide on the rational express fee.

The problem of cooperative package assignment to heterogeneous express stations is very challenging. First, we need to design a novel pricing structure of ES to enable the cooperative package assignment without revenue loss to express companies. Especially, there should be the increased cost at the ES since there is more work at the ES. Second, in order to optimize the joint cost of express fee and moving cost, we should decide on the set of packages assigned to any ES. However, the package set can be any subset of all packages. This means that finding the optimal package set of any ES needs exponential time. Moreover, the optimal algorithm or approximation algorithm (if exists) may be impractical to deal with the large-scale cooperative package assignment problem due to the high time complexity.

The main contributions of this paper are as follows:

- We present a cooperation model for express users and formulate the *cooperative package assignment (CPA)* problem for heterogeneous express stations.
- We propose a pricing structure of ES for the cooperation modelto guarantee the revenue of express companies.
- We propose a $\frac{\ln n+1}{1-\varepsilon}$-approximation algorithm for the *CPA* problem based on the greedy approach using submodular function minimization [17].
- We model the large-scale *CPA* problem as a coalition formation game, which has at least one *Nash Equilibrium*. We propose the *CPA-game algorithm* (*CPAGA*) and show that *CPAGA* finally converges to a pure *Nash Equilibrium*.

The rest of the paper is organized as follows. Section II presents the system model and formulates the *CPA* problem. The approximation algorithm for *CPA* problem is proposed in Section III. Section IV presents *CPAGA* to optimize the large-scale *CPA* problem. Performance evaluation is shown in Section V. We conclude this paper in Section VI.

II. System Model

We consider a cooperative package assignment system consisting of an express platform, a set $M = \{1, 2, \cdots, m\}$ of m express stations and a set $N = \{1, 2, \cdots, n\}$ of n users, and each is with a package to deliver. All computation of the system is made by the express platform, which resides in the cloud server. To simplify the notation, we reuse the notation i and N to denote the package delivered by user i and the package set delivered by all users, respectively. The cooperative package assignment system is developed to increase business and is operated by the alliance of express companies. First, the packages are lumped at the ES. We consider that the packages in the cooperative package assignment system have the same destination distribution center. Otherwise, they cannot be transported together, and the transportation cost will increase. Then, the cooperative packages are unpacked and sorted at the distribution center. Finally, the unpacked packages will be delivered to the different ESs. Usually, one city only has one distribution center, thus the cooperation package assignment problem is ubiquitous.

We consider that the ESs are operated by multiple express companies, and each ES $j \in M$ is with a location l^j in a 2-D surface. Each user $i \in N$ submits the information $B_i = (\chi_i, l_i, w_i)$ to the platform, where χ_i, l_i, w_i are the unit moving cost, current location and weight of the package of user i, respectively.

Next, we present the pricing rule, cooperation model, cost allocation scheme and problem formulation. The frequently used notations are listed in Table II.

A. Pricing Rule

We use the express pricing rule adopted in practice [18], [19], [20], [21]. The express fee ϕ_i^j of any user $i \in N$ at any ES j in the non-cooperative express mode is defined as:

$$\phi_i^j = \begin{cases} p_j^f, & w_i \le H_j^f \\ p_j^f + (w_i - H_j^f)p_j^c, & w_i > H_j^f \end{cases} \tag{1}$$

TABLE II
FREEQUENTLY USED NOTATIONS

Symbol	Description
M, m	set of ESs, number of ESs
N, n	set of users/packages, number of users/packages
B_i	information submitted by the users
χ_i	unit moving cost
l_i, l^j	location of user i, location of ES j
$d(l_i, l^j)$	distance between l_i and l^j
w_i	weight of user i's package
ϕ_i^j	express fee of user i at ES j in non-cooperative mode
p_j^f, p_j^c	first heavy price of ES j, continued heavy price of ES j
H_j^f	threshold weight of ES j
G_j	set of packages assigned to ES j (coalition of ES j)
$\mathbf{G}$	set of package set of all ESs (coalition structure)
$\phi(G_j)$	total express fee of users in G_j
$c(G_j)$	comprehensive cost of G_j
$p(G_j)$	cooperation cost of G_j
$\phi_i(G_j)$	express fee of user $i \in G_j$
$c_i(G_j)$	comprehensive cost of user $i \in G_j$
ε	search precision
a_i, a_{-i}	strategy of user i, strategies of users except i
$u_i(a_i, a_{-i})$	utility of any user i
$\succ_i$	preference order of user i
$(a_1^*, a_2^*, ..., a_n^*)$	*Nash Equilibrium* of *CPA-game*
$f(a_i, a_{-i})$	potential function of *CPA-game*

where p_j^f and p_j^c are the first heavy price per *kg* and continued heavy price per *kg* of ES j, respectively. H_j^f is the threshold weight of ES j.

Note that the other dimensions of the packages, such as volume, may be considered in the practical pricing rule, but the detail is not of academic interest. Thus, we only consider the weight of packages. Moreover, to the best of our knowledge, the pricing rules of all express companies satisfy the following inequality, which is an important observation.

$$p_j^f > p_j^c H_j^f \tag{2}$$

The package is called small package if its weight is no more than the threshold weight of the assigned ES. Otherwise, the package is called big package.

B. Cooperation Model

When the users cooperate at the same ES, there is increased cost at the ES since the cooperation brings additional workload, such as lumping packages, separating lumped packages and delivering packages to different ESs. Thus, we introduce the cooperation cost to compensate the increased cost of ESs.

Consider that G_j is the set of packets assigned to ES j. In the cooperation model, we consider that each package is a big package to the assigned ES, i.e., $w_i > H_j^f, \forall i \in G_j$. Thus the total express fee $\phi(G_j)$ of users in G_j can be calculated as:

$$\phi(G_j) = \begin{cases} p_j^f + (\sum_{i\in G_j} w_i - H_j^f)p_j^c + p(G_j), & if\ G_j \neq \emptyset \\ 0, & otherwise \end{cases} \tag{3}$$

where $p(G_j)$ is the cooperation cost of G_j.

The cooperation cost is a nonnegative, monotone and submodular function, which reflects the diminishing cooperation cost on the cooperative packages. Specifically, $p(G_j)$=0 if $|G_j| = 1$, i.e., there is no cooperation cost for the alone package in G_j. Note that $p(G_j)$ can be any nonnegative, monotone and submodular function. We use the log function as the cooperation cost in our simulations.

Essentially, our pricing structure is to charge the multiple packages as a single normal big package. The express fee of proposed pricing structure contains the express fee determined by the currently used pricing rule for the big normal package and the cooperation cost. So, the total payment to ESs is more than that for delivering a single normal big package. The revenue of ESs can be guaranteed if the cooperation cost can cover the extra cost, that is, the revenue of the express stations in cooperation model will not decrease comparing with delivering a single normal big package with same weight under current pricing rule.

Then, the comprehensive cost of G_j is the sum of express fee and moving cost of all users in G_j:

$$c(G_j) = \phi(G_j) + \sum_{i\in G_j} \chi_i \cdot d(l_i, l^j) \tag{4}$$

where $d(l_i, l^j)$ is the distance between l_i and l^j.

Note that the small package cooperation model satisfying $\sum_{i\in G_j} w_i \leq H_j^f$ can be formulated in a similar way.

Besides the above two models, there are other two possible cooperation models: (1) The individual weight is less than the threshold weight of ES, but the total weight is more than the threshold weight; (2) The package assigned to a ES can be either a small package or a big package. However, we do not take into consideration the above two cooperation models due to the following two main reasons:

(1) The sorting, storing, assembling, and transportation for small package and big package are quite different. From the economic perspective, the separated cooperation models studied in this paper avoid the additional cost for dealing with the hybrid packages.

(2) Even though the users may benefit from the two cooperation models, the comprehensive cost function $c(\cdot)$ in these two cooperation models is not a submodular function, and there is no approximation algorithm for the *CPA* problem (will be defined in Section II.D) so far. This problem would be solved by defining a new submodular comprehensive cost function. However, the new comprehensive cost function must deviate from the current pricing rule adopted in practice.

C. Cost Allocation

The cost allocation scheme aims to determine the actual expenditures of users in any set G_j in the proposed cooperative package assignment system.

We consider that the express fee $\phi_i(G_j)$ of any user $i \in G_j$ is proportional to the weight of its package:

$$\phi_i(G_j) = \phi(G_j)\frac{w_i}{\sum\limits_{i'\in G_j} w_{i'}} \tag{5}$$

Then, the comprehensive cost $c_i(G_j)$ of any user $i \in G_j$ is the sum of its express fee and moving cost:

$$c_i(G_j) = \phi_i(G_j) + \chi_i \cdot d(l_i, l^j) \tag{6}$$

D. Problem Formulation

The objective is minimizing the comprehensive cost of all users such that each package is assigned to exactly one ES. We refer to this problem as *Cooperative Package Assignment (CPA)* problem, which can be formulated as follows:

$$(CPA): \min_{\mathbf{G}} \sum_{j \in M} c(G_j) \tag{7}$$

$$\textbf{\textit{s.t.}} \quad N = \bigcup_{j \in M} G_j \tag{7-1}$$

$$G_j \cap G_{j'} = \emptyset, \forall j \neq j', j \in M, j' \in M \tag{7-2}$$

where $\mathbf{G} = (G_1, G_2, ..., G_m)$ is the set of package sets of all ESs. The constraint (7-1) ensures that all packages should be assigned. The constraint (7-2) ensures that each package can be assigned to exact one ES.

Note that if the cooperation cost is small enough, the comprehensive cost of all users under cooperation model must be lower than that under noncooperation model. This is because the packages in the same ES can cooperate by paying according to (6), and the comprehensive cost of this ES will always decrease.

III. Approximation Algorithm For CPA Problem

In this section, we present the *cooperative package assignment algorithm (CPAA)* to solve the *CPA* problem.

First of all, we give the following definition:

Definition 1. *(Nonnegative, monotone and submodular function): Given a finite ground set N and a real-valued set function $c: 2^N \to \mathbb{R}$, c is called nonnegative, monotone and submodular if and only if it satisfies the following conditions:*

- $c(\emptyset) = 0$ *and* $c(A) \geq 0$ *for all* $A \subseteq N$*;*
- $c(A) \leq c(B)$ *for all* $A \subseteq B \subseteq N$*;*
- $c(A \cup \{e\}) - c(A) \geq c(B \cup \{e\}) - c(B)$ *for all* $A \subseteq B \subseteq N$ *and* $e \in N \backslash B$.

Obviously, the comprehensive cost function $c(\cdot)$ defined in formula (4) is a nonnegative, monotone and submodular function based on our cooperation model given in subsection II.B and the fact of $p_j^f > p_j^c H_j^f$.

We attempt to find an optimal algorithm for the *CPA* problem. Unfortunately, as the following theorem shows, the *CPA* problem is NP-hard.

Theorem 1. *The CPA problem is NP-hard.*

Proof: Our *CPA* problem defined in (7) is equivalent to the *generalized facility location problem* (*GFLP*): There are a set M of facilities and a set N of clients. The connection cost of any client $i \in N$ to any facility $j \in M$ is $\chi_i \cdot d(l_i, l^j)$. The facility cost of any client $i \in N$ and any facility $j \in M$ is $\phi_i(G_j)$. The objective is to find an assignment of each client to an open facility to minimize the total cost incurred. The *GFLP* can be formulated as follows:

$$(GFLP): \min \sum_{j \in M} \phi_i(G_j) y_j + \sum_{j \in M} \sum_{i \in N} \chi_i \cdot d(l_i, l^j) x_{ij} \tag{8}$$

$$s.t. \sum_{j \in M} x_{ij} = 1, \forall o_i \in N \tag{8-1}$$

$$x_{ij} \leq y_j, \forall j \in M, \forall i \in N \tag{8-2}$$

$$x_{ij} \in \{0, 1\}, \forall j \in M, \forall i \in N \tag{8-3}$$

$$y_j \in \{0, 1\}, \forall j \in M \tag{8-4}$$

where y_j is a binary variate indicating whether facility j is open. x_{ij} is a binary variate indicating whether client i is assigned to facility s_j.

If $\phi_i(G_j)$ is a constant for each $j \in M$, the problem defined in (8) is simplified as the standard *facility location problem* (*FLP*) [16]. In the scenario of cooperative package assignment, $\phi_i(G_j)$ is related to the packages assigned to the facility j and is unknown in advance. Since the *FLP* is NP-hard, the *CPA* problem is NP-hard. ■

Since the *CPA* problem is NP-hard, it is impossible to compute the optimal solution in polynomial time unless P=NP. We turn our attention to the approximation algorithm design.

We propose an approximate algorithm for the *CPA* problem based on the greedy approach. Basically, we iteratively select an unassigned package set to one ES minimizing the ratio of the marginal comprehensive cost of the ES's package set to the number of newly covered packages (termed comprehensive cost effectiveness). However, the unassigned package set can be any subset of all unassigned packages, thus, the number of the unassigned package set is exponential. To address this problem, we use submodular function minimization [17] to find the unassigned package set with the best comprehensive cost effectiveness in polynomial time.

As illustrated in Algorithm 1, we find an unassigned package set S_j that minimizes the comprehensive cost effectiveness for each $j \in M$, by calling function $\mathbf{BinaryS}(\cdot)$ in each iteration (Line 7). Then we find the ES j with minimum ratio (Line 9). The unassigned package set S_j is merged into ES j's package set (Line 10). The iteration terminates when all packages are assigned.

Algorithm 1 : CPAA

Input: $N, M, B_i, \forall i \in N, p_j^f, p_j^c, H_j^f, \forall j \in M$

1: **for each** $j \in M$ **do**
2: $G_j \leftarrow \emptyset$**;**
3: **end for**
4: $N' \leftarrow N$**;** $\mathbf{G} \leftarrow (G_1, G_2, ..., G_m)$**;**
5: **while** $N' \neq \emptyset$ **do**
6: **for each** $j \in M$ **do**
7: $S_j \leftarrow \mathbf{BinaryS}(j, G_j, N')$**;**
8: **end for**
9: $j \leftarrow \arg\min_{j' \in M} \frac{c(G_{j'} \cup S_{j'}) - c(G_{j'})}{|S_{j'}|}$ **;**
10: $G_j \leftarrow G_j \cup S_j$**;** $N' \leftarrow N' \backslash S_j$**;**
11: **end while**
12: **return** $\mathbf{G}$**;**

The key operation of *CPAA* is to find the set $S \subseteq N'$ minimizing $\frac{c(G_j \cup S) - c(G_j)}{|S|}$. As mentioned above, the number of the unassigned package set is exponential of the size of N'. To minimize this ratio, we execute a binary search for the minimum value mid that there exists a set S such that $\frac{c(G_j \cup S) - c(G_j)}{|S|} \leq mid$, i.e,

$$c(G_j \cup S) - c(G_j) - mid|S| \leq 0 \tag{9}$$

Note that the first term of left side is a submodular function and the second term is a modular function. The second term is a constant when finding set S. The last term is a modular function. Thus, we can minimize the left side in polynomial time by using submodular function minimization, which can be solved by the strongly polynomial algorithm [17].

We execute the binary search by calling function $\mathbf{BinaryS}(\cdot)$, which is illustrated in Algorithm 2. Let low and $high$ be the indicator for left boundary and right boundary, respectively. We set $high = \frac{c(G_j \cup N') - c(G_j)}{|N'|}$ initially (Line 1), this is because $S = N'$ (assign all unassigned packages to ES j) is a feasible solution for minimizing $\frac{c(G_j \cup S) - c(G_j)}{|S|}$. So $\frac{c(G_j \cup N') - c(G_j)}{|N'|}$ is an upper bound of the value of $\frac{c(G_j \cup S^*) - c(G_j)}{|S^*|}$ indeed, where S^* is the optimal solution. We use the binary search (Lines 2-13) to find the set S. In each iteration, we use submodular function minimization to compute the minimum of $(c(G_j \cup S) - c(G_j) - mid|S|)$ (Line 3). The binary search terminates when the value of $(\frac{c(G_j \cup S) - c(G_j)}{|S|} - mid)$ satisfies the search precision $\varepsilon \in (0, 1)$ (Line 4).

Algorithm 2 : $\mathbf{BinaryS}(\cdot)$

Input: j, G_j, N'
1: $low \leftarrow 0$, $high \leftarrow \frac{c(G_j \cup N') - c(G_j)}{|N'|}$, $mid \leftarrow \frac{low + high}{2}$;
2: **while** (1) **do**
3: $\quad S \leftarrow \arg \min_{S' \subseteq N', S' \neq \emptyset} (c(G_j \cup S') - c(G_j) - mid|S'|)$;
4: $\quad$ **if** $|\frac{c(G_j \cup S) - c(G_j)}{|S|} - mid| \leq \varepsilon$ **then**
5: $\quad\quad$ **return** S;
6: $\quad$ **end if**
7: $\quad$ **if** $c(G_j \cup S) - c(G_j) - mid|S| \leq 0$ **then**
8: $\quad\quad high \leftarrow mid$;
9: $\quad$ **else**
10: $\quad\quad low \leftarrow mid$;
11: $\quad$ **end if**
12: $\quad mid \leftarrow \frac{low + high}{2}$;
13: **end while**

Theorem 2. *CPAA is a polynomial algorithm.*

Proof: We first analyze the time complexity of $\mathbf{BinaryS}(\cdot)$ (Algorithm 2). The binary search with search precision ε takes $O(\log \frac{high}{\varepsilon})$ time, where *high* is the right boundary of binary search. Minimizing submodular function (Line 3) takes $O(n^7 \log n)$ time if we use the strongly polynomial algorithm proposed in [17]. Algorithm 2 is dominated by Line 3. Thus, the running time of Algorithm 2 is $O(n^7 \log n \log \frac{high}{\varepsilon})$.

CPAA (Algorithm 1) is dominated by finding the unassigned package set S_j for all $j \in M$ (Lines 6-8). Since binary search (Line 7) takes $O(n^7 \log n \log \frac{high}{\varepsilon})$ time, the for-loop (Lines 6-8) takes $O(mn^7 \log n \log \frac{high}{\varepsilon})$ time. The while loop (Lines 5-11) is executed at most n times since there are n packages and each iteration of the loop will cover at least one package. Thus, the running time of *CPAA* is $O(mn^8 \log n \log \frac{high}{\varepsilon})$. ■

Theorem 3. *CPAA is a $\frac{\ln n + 1}{1 - \varepsilon}$-approximation algorithm of the CPA problem..*

Proof: We number the packages of N in the order that they were covered by *CPAA* resolving ties arbitrarily. Let $q_1, q_2, ..., q_n$ be this numbering. Assume $q_k, k = 1, 2, ..., n$ is covered by set S_j of ES j when the package set previously covered is G_j. Then the comprehensive cost effectiveness of q_k is

$$cost(q_k) = \frac{c(G_j \cup S_j) - c(G_j)}{|S_j|} \tag{10}$$

Let *OPT* be the optimal comprehensive cost of *CPA* problem. Consider the iteration in which q_k was covered, the package sets of optimal solution can cover the remaining packages in N' with comprehensive cost at most *OPT*. Therefore, among all package sets in the optimal solution, there must be one having comprehensive cost effectiveness at most $OPT/|N'|$, where $|N'| \geq n - k + 1$. Since was covered by set S_j of ES j with minimum comprehensive cost effectiveness in this iteration, it follows:

$$cost(q_k) \leq \frac{OPT}{|N'|} \leq \frac{OPT}{n - k + 1} \tag{11}$$

Since the comprehensive cost of each package set is distributed among the new packages covered, the total comprehensive cost of the package sets obtained by *CPAA* is equal to $\sum_{k=1}^{n} cost(q_k)$. We have:

$$\begin{aligned} \sum_{k=1}^{n} cost(q_k) &\leq \sum_{k=1}^{n} \tfrac{OPT}{n-k+1} = (1 + \tfrac{1}{2} + ... + \tfrac{1}{n})OPT \\ &\leq (\ln n + 1)OPT \end{aligned} \tag{12}$$

Thus, *CPAA* is $(\ln n + 1)$-approximation if it can find the optimal solution to minimize the comprehensive cost effectiveness for any ES. Considering the search precision $\varepsilon \in (0, 1)$, the binary search approximates the optimal comprehensive cost effectiveness within a factor of $1/(1 - \varepsilon)$. Thus, *CPAA* is $(\frac{\ln n + 1}{1 - \varepsilon})$-approximation. ■

IV. Optimizing Large-scale CPA Problem

Although *CPAA* is a polynomial algorithm, as shown by Theorem 2, the approximation algorithm still incurs high computing cost and is inefficient for the large-scale *CPA* problem with a number of packages. The large-scale cooperative package assignment can appear in densely populated areas, such as big residential community and central business district.

To address the issue, we propose a greedy algorithm. To show the convergency of the greedy algorithm, we formulate the *CPA* problem as a coalition formation game [22], termed *CPA-game*, which can improve the solution gradually. We will show that *CPA-game* algorithm, *CPAGA*, is much faster than *CPAA* in our simulations.

A. CPA-game

In *CPA-game*, the users are players. Each user $i \in N$ is with a strategy $a_i \in M$. The strategy space is ES set M. For any ES $j \in M$, G_j forms a coalition. Since all packages should be assigned and the comprehensive cost function is monotone, the coalition structure $\mathbf{G} = (G_1, G_2, ..., G_m)$ is a coalition partition of package set N actually.

Definition 2. *(Preference order): The preference order $\succ_i$ for any user $i \in N$ is defined as a complete, reflexive and* *transitive binary relation over the set of all feasible coalitions that user i can possibly form.*

A user decides to leave or to join a coalition based on the preference order. For example, for any user $i \in N$, $G_j \succ_i G_{j'}$ means that user i prefers being a member of coalition G_j rather than $G_{j'}$. Generally, the preference order influences the convergence and final coalition structure. In this paper, we consider the following order to minimize the comprehensive cost of all users. For each user $i \in N$ and any two coalitions G_j and $G_{j'}$, $j \neq j'$, we say that:

$$\begin{aligned} G_j \succ_i G_{j'} \Leftrightarrow \sum_{k \in G_j} c_k(G_j) - \sum_{k \in G_j \cup \{i\}} c_k(G_j \cup \{i\}) \\ > \sum_{k \in G_{j'}} c_k(G_{j'}) - \sum_{k \in G_{j'} \cup \{i\}} c_k(G_{j'} \cup \{i\}) \end{aligned} \tag{13}$$

This preference order means that the user i prefers the coalition with the minimum increase in comprehensive cost. This preference order cares about the total cost of coalition partition.

We define the utility of any user $i \in N$ in *CPA-game* as:

$$u_i(a_i, a_{-i}) = \sum_{k \in G_{a_i}} c_k(G_{a_i}) - \sum_{k \in G_{a_i} \cup \{i\}} c_k(G_{a_i} \cup \{i\}) \tag{14}$$

where a_{-i} is the strategies of users except i. The value of utility depends on the strategies of all users in the *CPA-game*. Accurately, G_{a_i} is a function of (a_i, a_{-i}). For convenience, we use G_{a_i} as a simplified expression of the function.

As illustrated in Algorithm 3, *CPAGA* follows the best-response dynamics, where players only choose the best response on the next round that would give them the highest utility [23]. At the beginning, each package is assigned to a random ES. At each round of iterations, each user selects an ES to maximize its utility. If the selected ES a_i is different from the current ES a_i^{old}, the user leaves the current ES and joins to the selected ES. Repeat the above process until no user changes its strategy. We will show that *CPAGA* finally converges to a pure *Nash Equilibrium (NE)*.

Note that the decision of each user can be made in both centralized way and distributed way. The distributed decision may happen if the platform does not have enough computation resource. In distributed way, the strategy of each user at each round is decided simultaneously by the user itself according to the strategy profile in last step publicized by the platform.

B. Analysis of NE and Acyclicity

We first introduce some closely related definitions about coalition formation game.

Definition 3. *(Nash Equilibrium): A set of strategies $(a_1^*, a_2^*, ..., a_n^*)$ is a Nash Equilibrium of the CPA-game if for any user i,*

$$u_i(a_i^*, a_{-i}^*) \geq u_i(a_i, a_{-i}^*), \forall i \in N \tag{15}$$

for any a_i, where u_i is defined in (14).

Definition 4. *(Exact Potential Game): The game is an exact potential game if and only if there exists a potential function $f(a_i, a_{-i}), \forall i \in N$ such that:*

$$f(a_i, a_{-i}) - f(a_i', a_{-i}) = u_i(a_i, a_{-i}) - u_i(a_i', a_{-i}) \tag{16}$$

for every $a_i, a_i' \in M$, and $a_{-i} \in A_{-i}$, where A_{-i} is the strategy set of users except i.

Algorithm 3 : CPAGA

Input: $N, M, B_i, \forall i \in N, \varphi_j, p_j^f, p_j^c, H_j^f, \forall j \in M$

for each $i \in N$ **do**
  $a_i \leftarrow Uniform[1, m]$;
end for
repeat
  $switcher \leftarrow 0$;
  for each $i \in N$ **do**
    $a_i^{old} \leftarrow a_i$;
    $a_i \leftarrow \arg\max_{a_i' \in M} u_i(a_i', a_{-i}')$;
    if $a_i \neq a_i^{old}$ **then**
      $G_{a_i} \leftarrow G_{a_i} \cup \{i\}$;
      $G_{a_i^{old}} \leftarrow G_{a_i^{old}} \backslash \{i\}$;
      $switcher \leftarrow 1$;
    end if
  end for
until $switcher \neq 1$;
return G;

For our *CPA-game*, we have the following theorem.

Theorem 4. *CPA-game has at least one Nash Equilibrium and CPAGA finally converges to a Nash Equilibrium.*

Proof: The utility change of any user $i \in N$ from a_i to a_i' is:

$$\begin{aligned} & u_i(a_i, a_{-i}) - u_i(a_i', a_{-i}) \\ & = \sum_{k \in G_{a_i}} c_k(G_{a_i}) - \sum_{k \in G_{a_i} \cup \{i\}} c_k(G_{a_i} \cup \{i\}) \\ & \quad - (\sum_{k \in G_{a_i'}} c_k(G_{a_i'}) - \sum_{k \in G_{a_i'} \cup \{i\}} c_k(G_{a_i'} \cup \{i\})) \end{aligned} \tag{17}$$

We define the potential function f as:

$$f(a_i, a_{-i}) = -\sum_{a_k \in M} \sum_{k \in G_{a_k}} c_k(G_{a_k}) \tag{18}$$

which is the opposite of sum of the all users'comprehensive cost. The above function is known as *Rosenthal's potential function* [24].

Since the change of user i's ES selection only affects the users in G_{a_i} and $G_{a_i'}$, the change of the potential function caused by its unilateral change is given by:

$$\begin{aligned} & f(a_i, a_{-i}) - f(a_i', a_{-i}) \\ & = -(\sum_{k \in G_{a_i} \cup \{i\}} c_k(G_{a_i} \cup \{i\}) - \sum_{k \in G_{a_i}} c_k(G_{a_i})) \\ & \quad - (\sum_{k \in G_{a_i'}} c_k(G_{a_i'}) - \sum_{k \in G_{a_i'} \cup \{i\}} c_k(G_{a_i'} \cup \{i\})) \\ & = u_i(a_i, a_{-i}) - u_i(a_i', a_{-i}) \end{aligned} \tag{19}$$

We can see from formula (19) that the change of utility function caused by any player's unilateral deviation is the same as the change of the potential function. Thus, according to Definition 4, the *CPA-game* is an exact potential game, which exhibits several nice properties, and the most important one is that every exact potential game has at least one pure *NE*. Thus, *CPA-game* has at least one pure *NE*.

Based on the lemma 2.3 in [24], every exact potential game with finite strategy sets has the *Finite Improvement Property (FIP)*; that is, unilateral improvement dynamics is guaranteed to converge to a pure *NE* using a finite number of steps. Thus *CPAGA* finally converges to a pure *NE*. ■

Note that *CPAGA* minimizes the total comprehensive cost of all users gradually since it aims to maximize the potential function, which is the opposite of total comprehensive cost.

V. Performance Evaluation

We have conducted simulations to investigate the performance of *CPAA* and *CPAGA* based on the real experience data. Due to the space limit, we only give the simulation results of big package cooperation model. Note that the small package cooperation model follows the same cost allocation scheme and assignment algorithms of big package cooperation model.

A. Simulation Setup

We compare our algorithms with the following four benchmark algorithms:

- *NC (nearest cooperation):* Each user chooses the nearest ES and follows the same cooperative pricing rule of *CPAA*.
- *NN (nearest noncooperation):* Each user chooses the nearest ES and pays the express fee according to the pricing rule of the ES independently. Note that this method of package assignment works in reality at present.
- *BC (best cooperation):* Each user chooses the best ES based on the comprehensive cost (without consideration of cooperation cost) independently and then follows the same cooperative pricing rule of *CPAA*.
- *OPT:* Optimal solution of *CPA* problem. We find the optimal solution by enumerating all possible partitions of users.

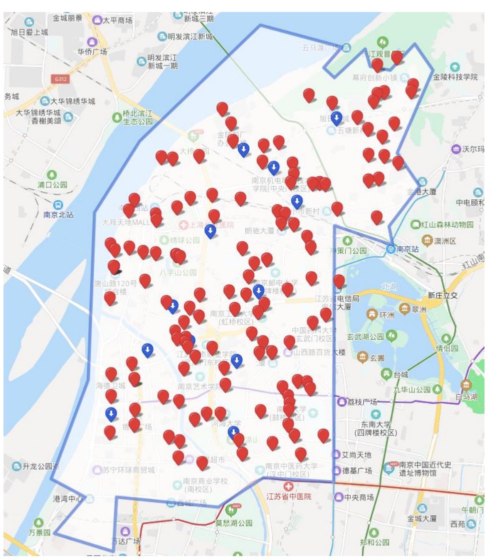


Fig. 2. Distribution of ESs and users in Gulou district of Nanjing.

For our simulations, we use the real distribution of ESs and users in Gulou district of Nanjing. As shown in Fig. 2, there are 12 heterogeneous ESs with different prices. We take the residential communities as the users since they have the fixed locations and randomly choose 120 residential communities in Gulou district. The weight of package is uniformly distributed over [1kg, 2kg]. For any ES $j \in M$, we use the following log function as the cooperation cost:

$$p(G_j) = \begin{cases} 0 & |G_j| \leq 1 \\ 2\log(|G_j|), & |G_j| > 1 \end{cases} \tag{20}$$

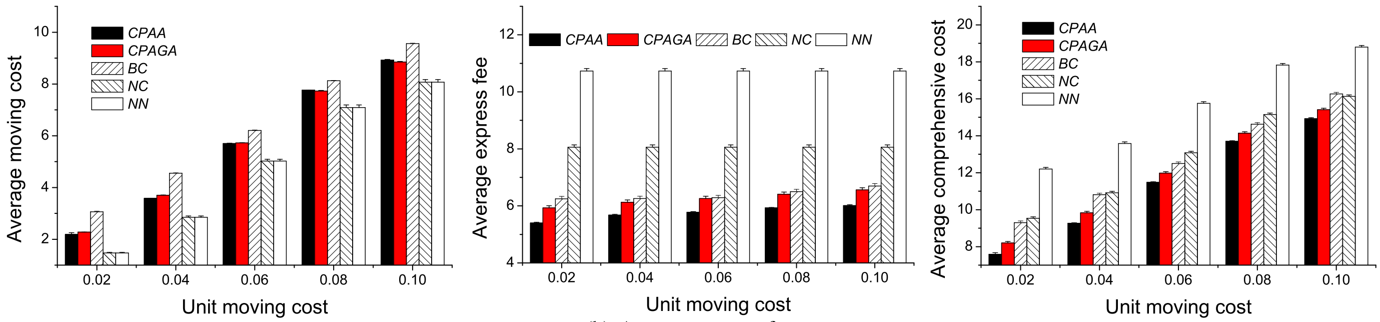
The default unit moving cost and search precision are 0.06 and 0.3, respectively. The unit of cost is Chinese yuan. We will vary the value of the key parameters to explore the impacts on designed algorithms. All the simulations are run on a Windows machine with Intel(R) Core(TM) i7-7560U CPU and 16 GB memory. Each measurement is averaged over 100 instances.

B. Cost

We first vary the unit moving cost from 0.02 to 0.1. As shown in Fig. 3, the moving cost of all five algorithms increases accordingly. The express fee of *CPAA*, *CPAGA* and *BC* increases slightly with the increasing unit moving cost. This is because when the moving cost increases, the users tend to move to the nearby ESs to minimize the comprehensive cost, reducing the cooperation opportunities. Note that the express fee of *NC* and *NN* doesn't change since each user always chooses the nearest ES. We can see from Fig. 3(c), the comprehensive cost of noncooperation algorithm is much higher than those of cooperation algorithms. Both of *CPAA* and *CPAGA* show outstanding advantage in terms of comprehensive cost. *CPAA* reduces the average comprehensive cost by 11.1%, 13% and 28.1% compared with *BC*, *NC* and *NN*, respectively. The performance gap between *CPAGA* and *CPAA* is small, and the average comprehensive cost of *CPAGA* is only 4.73% higher than *CPAA*. Note that *BC* has lower comprehensive cost than that of *NC* since it assigns the best ES to the users based on the comprehensive cost in noncooperation setting.

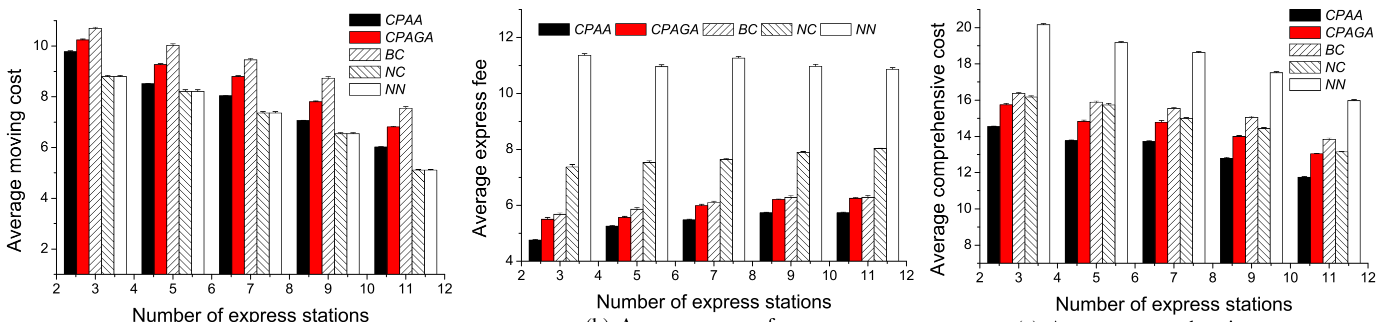
As shown in Fig. 4, the moving cost of all algorithms decreases when there are more ESs since the users can choose the closer ESs. The express fee of *CPAA*, *CPAGA*, *BC* and *NC* increases slightly with the increasing number of ESs because some added ESs help users to reduce the moving cost and disperse the users to more ESs, reducing the cooperative surplus. However, the express fee of *NN* is affected only by the pricing rules of added ESs and almost does not change. Overall, the comprehensive cost of all algorithms tends to decrease when we increase the number of ESs.

To test the scalability of proposed algorithms, we increase the number of users from 20 to 120. As shown in Fig. 5, the express fees of *CPAA*, *CPAGA*, *BC* and *NC* decreases significantly when there are more users. This is because the number of cooperative users in each ES increases averagely, increasing the cooperative surplus. Attracted by the cooperative surplus, users of *CPAA* and *CPAGA* tend to further ESs and the moving cost increases slightly. For the fixed ESs, the choice of ES in *BC*, *NC* and *NN* doesn't affected by the cooperative surplus. Thus, the moving cost of *BC*, *NC* and *NN* almost doesn't



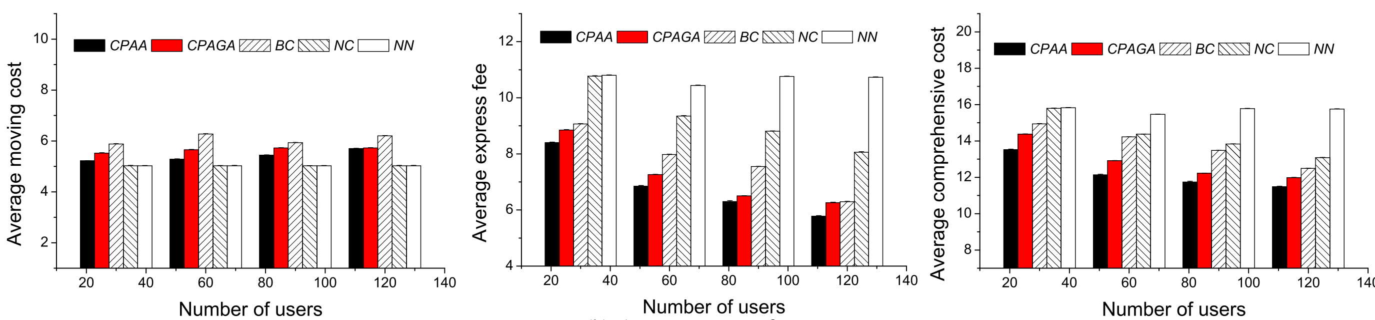
(a) Average moving cost (b) Average express fee (c) Average comprehensive cost

Fig. 3. Impact of unit moving cost (χ_i)



(a) Average moving cost (b) Average express fee (c) Average comprehensive cost

Fig. 4. Impact of number of express stations (m)



(a) Average moving cost (b) Average express fee (c) Average comprehensive cost

Fig. 5. Impact of number of users (n)

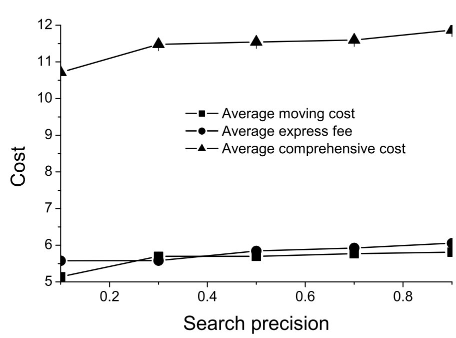


Fig. 6. Impact of search precision (ε) on *CPAA*.

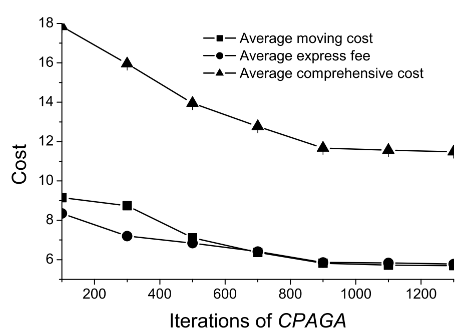


Fig. 7. Impact of iterations on *CPA-game*.

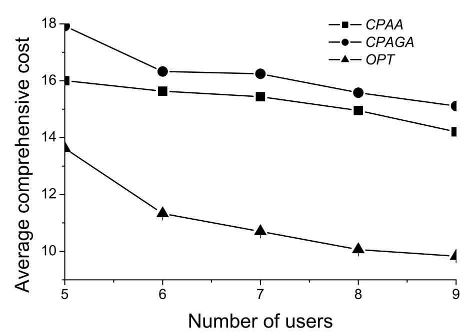


Fig. 8. Comparison with optimal solution.

change. From Fig. 5(c), we can see that the comprehensive cost of cooperation algorithms decreases with increasing number of users. Furthermore, we can see that *CPAA* and *CPAGA* show more advantages in terms of average comprehensive cost in the large-scale package assignment system.

Fig. 6 shows the impact of search precision on the cost of *CPAA*. With the improvement of accuracy, the cost of *CPAA* decreases accordingly. Fig. 7 depicts the comprehensive cost of *CPAGA* with the iterations to verify the convergence of *CPAGA*. We can see that the outputs become stable after 900 iterations when there are 120 users and 12 ESs. We compare the performance of our algorithms with the optimal solution in small settings. We also measure the performance gap between our algorithms and *OPT*. As shown in Fig. 8, the comprehensive cost of *CPAA* is 1.36 times the comprehensive cost of *OPT* on average.

C. Payment

We have conduct the simulations to show how much is paid to the express station under the cooperation model comparing with currently used pricing rule for a single normal big package. We measure the average payment to ESs, i.e., the ratio of total express fee of all users to the number of ESs. We compare *CPAA* with the delivering a single normal big package over same package assignment of *CPAA* (termed *CPAA-single*) and the noncooperation model over same package assignment of *CPAA* (termed *CPAA-noncooperation*). The similar comparisons are made for *CPAGA*. Though the payment to ESs of *CPAA* and *CPAGA* is lower than the corresponding noncooperation models, we can see from Fig. 9 that *CPAA* and *CPAGA* can increase the payment by 13.2% and 13.5% comparing with *CPAA-single* and *CPAGA-single*, respectively.

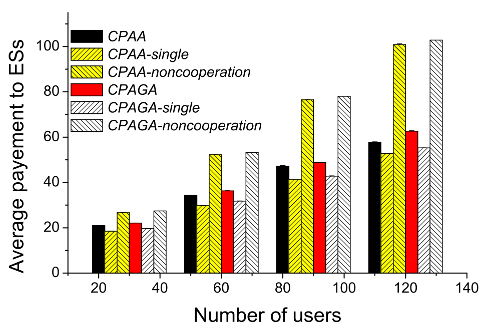


Fig. 9. Average payment to the express stations

D. Running Time

The running time of *CPAA*, *CPAGA* and *OPT* (only for small settings) are shown in Table III. We can see that the running time grows rapidly with increasing number of users. However, *CPAGA* shows great scalability and can output the solution within 1 second with 120 users.

TABLE III
RUNNING TIME OF *CPAA*, *CPAGA*, AND *OPT*

Number of users	***CPAA*** **(ms)**	***CPAGA*** **(ms)**	***OPT*** **(ms)**
5	91.42	1.65	96358.24
6	494.18	2.67	226041.31
7	1759.19	7.52	563728.95
8	3943.65	14.03	729372.77
9	9650.38	19.86	1506368.07
30	10652222.24	1146.67	
60		307.89	
90		678.87	
120		989.92	

VI. CONCLUSION AND FUTURE WORK

In this paper, we have studied the cooperative package assignment with heterogeneous express stations. We have formulated *CPA* problem to minimize the total comprehensive cost of cooperative users, which consists of express fee and moving cost. We have designed a $\frac{\ln n+1}{1-\varepsilon}$-approximation algorithm of *CPA* problem. Furthermore, we have modeled the large-scale *CPA* problem as coalition formation game and presented *CPAGA*, which finally converges to a pure Nash Equilibrium. Through extensive simulations, we demonstrate that *CPAA* and *CPAGA* show great advantages in terms of comprehensive cost (28.1% and 19.9% lower than the non-cooperation mode adopted in reality, respectively). *CPAGA* shows great scalability and is more suitable for large-scale cooperative package assignment system.

Notice that our *CPAA* considers that the users are unselfish. In reality, the users are usually selfish. This motivates us to develop the cost allocation scheme, which belongs to the core [25]. Moreover, from the perspective of ES, the ES's revenue is affected by the users' strategies of ES selection. Besides introducing the cooperation cost, the dynamic pricing scheme is possible to incentive ESs by using the game theory approach, such as Stackelberg game [26] and bargaining game [27].

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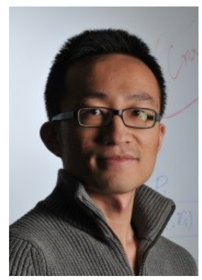

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