Application of Ant Colony Optimization for Buyer Coalition in e-Marketplaces

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***Abstract*—** Several heuristic algorithms were developed to optimization problems. Ant colony optimization (ACS) based on real ants for finding good solutions represents an important branch of such metaheuristics. It has been used successfully in many different areas. However, it is rarely used in forming the buyer group in electronic marketplaces. In this paper, the proposed approach, called BCF_2ACO, applies two ant colony optimizations to searches for the best way to form a buyer coalition according to the total utility earned from sellers. The first ant colony searches the best disjoint subsets of all buyers based on the total utility obtained by the works of the second colony of artificial ants. The second ant colony also searches the way to purchase several units of goods within bundles of items to obtain the best total utility to partitioned groups of buyers. Though the ACO has no guarantees to find the optimal solution, but our simulation of BCF_2ACO algorithm shows that the proposed algorithm searches the solution better than the results obtained by genetic algorithm (GA) called GroupPackageString scheme in the terms of the global optimal solution.

***Keywords*—**Ant colony optimization, Buyer coalition, Coalition structure, Simulation.

I. INTRODUCTION

MOST buyers prefer to obtain a deduction from the price list offered by a seller in return for payment. One common shopping strategy which buyers are likely to make is a buying group because a large group of buyers has more negotiating power. Moreover, they can advantageously negotiate with sellers to get the great discount on their purchases. To date, sellers prefer to put their products on the electronic marketplaces because it is one of the big channels to sell their products in a large number. And, several commercial websites such as http://buy.yahoo.com.tw and https://shops.godaddy.com usually offer the volume discount for customers if the number of selling is big. So, there exist many schemes focusing on forming a buyer coalition in the electronic market with the aim of gaining the great discount for buying a large number of goods. Several buyer coalition schemes have been developed with various goals. For example, the work of Ito, Hiroyuki, and Toramatsu in [1] presented an agent-mediated electronic market by group buying scheme. Buyers or sellers can sequentially enter into the market to make their decisions. Tsvetovat, Sycara,, Chen, and Ying [2] have investigated the use of incentives to create buying group. Yamamoto, and Sycara, presented the GroupBuyAuction scheme [3] for forming buyer coalition base on item categories. Then, the paper of Masaki, Tokuro, and Takayuki [4] presented an optimal coalition formation among buyer agents based on a genetic algorithm (GA) with the purpose of distributing buyers among group-buying site optimally to get good utilities. These strategies focus on a situation where different buyers participate in one group to purchase goods at low cost. So, a whole group of buyers can advantageously deal with sellers to gain more discount for a large volume of items. In addition, an interesting paper in [15] presents a conceptual model, which is useful for a coalition formation and an ontology used in an E-learning multiagent architecture.

However, there exists strategy called coalition structure (CS) in which a whole group can be partitioned into smaller sub-groups to achieve something more efficiently than they could accomplish in the whole group. In generality, CS is able to maximize the utility of the coalitions, but often the number of coalition structures is too large to allow for the exhaustive search for the optimal one [4]. Furthermore, finding optimal coalition structure is NP-complete [5].

In this paper, given a set of n buyers, $B = \{b_1, b_2,\dots, b_n\}$ and a subset or coalition $C\subseteq B$, there are two challenging stages involving in this paper:

1. Search disjoint subsets of all buyers of which the union of subsets equals B through the coalition structure for the group buying.
2. Calculation coalition value: the value of a coalition is the total utility of the group buying. The utility of each coalition C is obtained from sellers by purchasing goods. And, the sum of all the coalitions that would be formed is the total utility of the group buying. The experimental results are compared with result derived with the GroupPackageString scheme [6].

There are seven sections to this paper including this introduction section. The rest of the paper is organized as follow. Section 2 outlines the group buying with bundles of items including the motivated problems in detail. Section 3 details the problem formulation to buyer formation with bundles of items and the basic definitions used in this paper. Section 4 describes the ACO background. The details of the BCF_2ACO algorithm show in Section 5. The experimental setup and the discussion of results obtained from the empirical study are provided in Section 6. Finally, the conclusion and future work are in the last section.

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II. Outline of Group Buying with Bundles of Items

In electronic marketplaces, sellers have more opportunity to sell their products in a large number if their websites are well-known among buyers. Moreover, the pricing strategy of sellers is one of the reasons that might expedite the selling volume. Some sellers simultaneously make a single take-it-or-leave-it price offer to each unassigned buyer and to each buyer group [7]. The discount policy of sellers based on the number of items bundled in the package. Product bundling is combining two or more products or services together, creating differentiation, greater value and therefore enhancing the offering to the customer. Bundling is based on the idea that consumers value the grouped package more than the individual items. Basically, there are two kinds of product bundling, pure bundling and mixed bundling. Pure bundling occurs when a consumer can only purchase the entire bundle or nothing, mixed bundling occurs when consumers are offered a choice between the purchasing the entire bundle or one of the separate parts of the bundle. In this paper, an example given to describe motivation for this research is described below.

Suppose a seller in the e-marketplace prepares a large stock of goods and makes some packages of bundling packages. The example of price list offered by one seller is shown in table 1. And, the seller has four kinds of products, which are facial toner, body lotion, hair conditioner, and hair shampoo. The seller has made some special offers to get the big volume of selling. Typically, a buyer has seen the price list provided by sellers before making orders. For instance, the seller offers to sell a pack of facial toner in the package p_1 with the regular price of \$15.0. However, the same product of facial toner is also in the package p_2. It costs \$58.0 for six packs of facial toner. The average price of each facial toner is about 58.0/6 = 9.67 dollars/bottle, which is 15.0-9.67 = 5.33 dollars/bottle cheaper than a sing-bottle of facial toner in package P_1. If one buyer needs to buy this facial toner, the buyer might want to get this facial toner at the price of 9.67. However, due to personal budget, buyer b_1 prefers to buy only three pack of facial toner. Suppose the buyer b_1 is willing to pay for each of facial toner at \$10.00 as seen in Table 2, while the other buyers need to purchase different products. If b_1 goes straight to buy those products without joining in the group buying, of course, it might be impossible for b_1. Also, it might be difficult for other buyers.

TABLE I. The price list example

Package No.	Products				Price ($)
	Facial toner	*Body lotion*	*Hair conditioner*	*Hair shampoo*	
P_1	Pack of 1	-	-	-	15.0
P_2	Pack of 6	-	-	-	58.0
P_3	-	Pack of 1	-	Pack of 1	21.0
P_4	-	-	Pack of 1	Pack of 1	30.0
P_5	-	-	-	Pack of 1	15.0
P_6	-	-	Pack of 1	-	17.0
P_7	-	Pack of 1	-	-	9.5

TABLE II. A sample of Buyers' reservation

Buyers	Buyer's Order (Number of item × (price $))			
	Facial Toner	*Body Lotion*	*Hair Conditioner*	*Hair Shampoo*
b_1	3 x (10.0)	-	-	-
b_2	1 x (11.0)	1 x (7.0)	-	-
b_3	-	-	-	2 x (14.5)
b_4	2 x (11.0)	-	1 x (15.0)	-

One strategy that buyers need to do is to join their requests so that they can buy bigger packages, which are normally cheaper than the single-items package. If the group has decided to buy one of package P_2, P_3, and P_4, the total amount of money that the group needs to pay for the seller is 58.0+21.0+30.0 = 109.0 dollars. Additionally, the total utility eared form the group buying is (3*10+1*11+1*7+2*14.5+2*11+1*15)-109= 114-109 = 5\$. However, in forming a group, there are some situations that buyers cannot really be in the group. For instance, if there is a new buyer called b_5 joining in the group buying, but b_5 requests only two facial toners at the price of \$11. For the best way, the group might need to buy two of P_1 for the buyer b_5. The new total utility of the group is (114+2*11)-(109.0+2*15) = -3\$. So, it might be better to form the group buyer without the buyer b_5. Only four buyers of b_1, b_2, b_3 and b_4 are selected to be in the group buying.

III. Problem Formulation

The objective of our paper is to maximize the utility of the buyer coalition as much as possible; the following terms and algorithm processes are needed to define.

The coalition is a temporary alliance of buyers for a purpose of obtaining the best utility. Let $B = \{b_1, b_2,\ldots,b_n\}$ denoted the collection of buyers. Each buyer wants to purchase several items posted by the specific seller in e-marketplaces. The seller has made special offers within a set of packages, denoted as $P = \{P_1, P_2,\ldots, P_k\}$. The price per item is a monotonically decreasing function when the size of the package is increasing big, an each package is associated with the set of prices, denoted Price = $\{price_1, price_2,\ldots, price_k\}$, where the $price_k$ is an item list denoted by a vector $\{g^{ik}_1\ g^{ik}_2,\ldots, g^{ik}_j\}$. If any goods g_j is not available in the $package^j_k$ of seller s_i, $g^{ik}_i = 0$. Each buyer b_m needs to buy some items offered by sellers, denoted as $Q_m = \{q^m_1\ ,q^m_2,\ldots,q^m_j\}$, where q^m_j refers to the quantity of items g_j of b_m. If $q^m_j = 0$, it means that buyer b_m does no request to purchase goods g_j. Also, any buyer b_m places a reservation price[1] for each particular goods associated with Q_m, denoted as $Rs_m = \{rs^m_1, rs^m_2,\ldots,rs^m_j\}$ where $rs^m_h \geq 0$, $1 \leq h \leq j$. The b_m's utility gained from buying q_m of g_j at the $price_j$ as $(rs^m_j - price_j)q_m$, so the total utility of the group is defined as follow:

[1] It represents the maximum price that he or she is willing to pay for one unit of a good or service [19]. There is an evidence of growing interest in advancing the understanding and measurement of the construct, particularly in e-marketing [20].

$$U = \sum_{b_m \in B} \sum_{q_m \in Q_m} (rs_j^m - price_j) q_m \cdot \quad (1)$$

However, for a set of n buyers, B = {b_1, b_2,…, b_n} and a coalition $C \subseteq B$, A coalition structure CS is a partition of B of which each buyers of B belongs to exactly one coalition and some buyers may be alone in their coalitions. Note that there are 2^n-1 possible coalition structures for n buyers [5]. For example, if B = {b_1, b_2, b_3}, there are seven possible coalitions:

{b_1},{b_2},{b_3},{b_1,b_2},{b_1,b_3},{b_2,b_3},{b_1,b_2,b_3}

and five possible coalition structures:

{{b_1},{b_2},{b_3}},{{b_1},{b_2,b_3}},{{b_2,{b_1,b_3}},
{{b_3},{b_1,b_2}},{{b_1,b_2,b_3}}.

The value of a coalition structure is

$$V(CS) = \sum_{C \in CS} v(C, CS) \cdot \quad (2)$$

where $v(C,CS)$ is the total utility of the group calculated by (1). And, the optimal coalition structure is noted as

$$CS^* = \arg \max_{CS \in M} V(CS) \cdot \quad (3)$$

In the paper of Sandholm *et al.* [5], the value of coalition structure $v(C,CS)$ is positive. However, in this paper, the value of $v(C,CS)$ is possible to be negative because the result of the poor formation could causes a bad utility. The coalition structure of four buyers based on Sandholm *et al.* is represented in Fig. 1.

IV. Ant Colony Optimization Background

Ant colony optimization (ACO) algorithms are inspired by the behavior of real ants for finding good solutions to combinatorial optimization. The first ACO algorithm was introduced by Dorigo and Gambardella [8], [9] in 1997 which known as Ant System (AS). ACO applied to classical NP-hard combinatorial optimization problems, such as the traveling salesman problem [10], the quadratic assignment problem (QAP) [11], and the shop scheduling problem and mixed shop scheduling [12]. Also, reference [16] adopts ant colony algorithm (ACA) with positive feedback to intelligent search and global optimize parameters of equivalent circuit. Additionally, it has been used successfully in wireless sensor network [17] and the Protein Side Chain Packing Problem [18].

In nature, real ants are capable of finding the shortest path from a food source to their nest without using visual cues [13], [14]. In ACO, a number of artificial ants build solutions to an optimization problem while updating pheromone information on their visited tails. Each artificial ant builds a feasible solution by repeatedly applying a stochastic greedy rule. While constructing its tour, an ant deposits a substance called pheromone on the ground and follows the path by previously pheromone deposited by other ants. Once *all* the *m* ants have completed their tours, the ant which found the best solution deposits the amount of pheromone on the tour according to the pheromone trail update rule. The best solution found so far in the current iteration is used to update the pheromone information. The pheromone τ_{ij}, associated with the line joining i and j, is updated as follow:

$$\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k, \quad (4)$$

where ρ is the evaporation rate which $\rho \in (0,1]$. The reason for this is that old pheromone should not have too strong an influence on the future. And $\Delta\tau_{ij}^k$ is the amount of pheromone laid on a line (i, j) by an ant k:

$$\Delta\tau_{ij}^k = \begin{cases} Q/L_k & \text{If line (i, j) is used by ant k.} \\ 0 & \text{otherwise,} \end{cases} \quad (5)$$

where Q is a constant, and L_k is the length of the tour performed by the ant k.

In constructing a solution, it starts from the starting city to visit an unvisited city. When being at the city i, ant k selects the city j to visit through a stochastic mechanism with a probability p_{ij}^k given by:

$$p_{ij}^k = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{c_{il} \in N_i^k} \tau_{il}^{\alpha} \cdot \eta_{il}^{\beta}} & \text{if } j \in N^i{}_k \\ 0 & \text{otherwise,} \end{cases} \quad (6)$$

where $N^i{}_k$ is a set of feasible neighborhood of the ant k, representing the set of cities where ant k has not been visited. Both α and β are two parameters determining the relative influence of pheromone trail and heuristic information. And η_{ij} is calculated by:

$$\eta_{ij} = \frac{1}{d_{ij}}, \quad (7)$$

where d_{ij} is the length of the tour performed by the ant k between cities i and j..

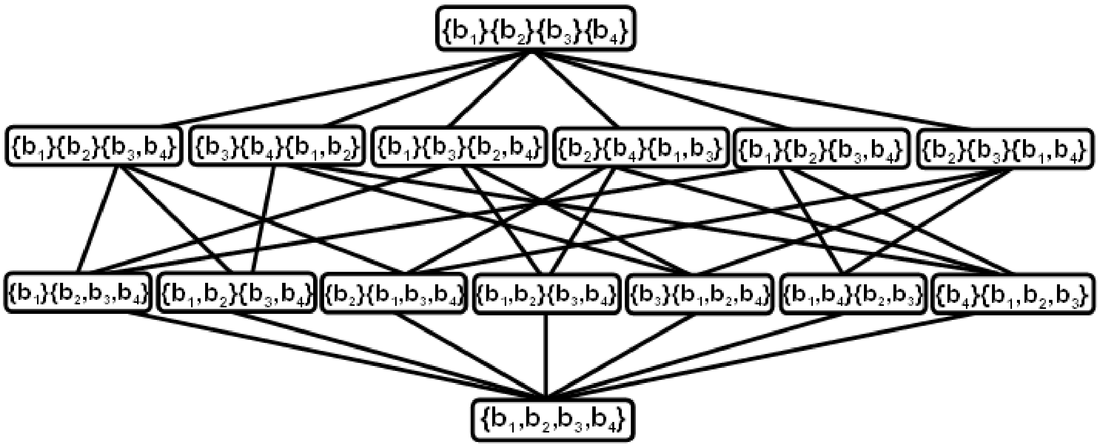


Fig. 1 Coalition structure of 4 buyers.

V. FORMING BUYER GROUP WITH BUNDLES OF ITEMS BY ANTS

In this paper, there are two ant colonies simultaneously working for forming group buying with bundles of items. The first colony searches the paths for disjoint subsets of all buyers based on the subset's utility, which is calculated by the work of the second colony. The procedures are described as follows.

A. *First Ant Colony (Ant1):*

It is the creation of paths through the disjoint subsets of all buyers. In common ant colony optimization for forming buyer group, the problem must be represented as graph where the optimum subgroup of buyers can be defined in a certain way through the graph.

Given a set of buyers B = {b_1, b_2…, b_n} divided into m subgroups, $C_1, C_1, ..., C_m$, where $\prod_{k=1}^{m} C_k = \phi$, $\bigcup_{k=1}^{m} C_k = B$, each C_k, $1 \le k \le m$. During the walk of any ants, the closed path is created called BCF_2ACO graph. There are two types of lines used in the BCF_2ACO graph as described below.

1. Solid line: if b_i and b_j, $i \neq j$, are in the same group, a solid line is used to join b_i to b_j. However, it is not necessary to have a direct line joining between b_i and b_j.
2. Dotted line: if C_k and C_h are two different subgroups where $C_k \cap C_h = \emptyset$, then there is at least one dotted line from a member in C_k to the other in C_h.

For example, Let a set of three buyers B = {b_1, b_2, b_3}. As seen in Fig. 2, there are six possible lines; which are three of solid lines and dotted lines.

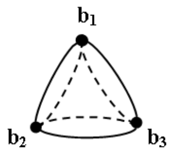


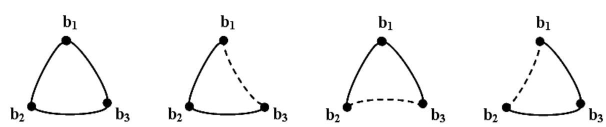
Fig. 2 Representing relationship of buyers (n =3) in graph.

Rules for creating BCF_2ACO graph for n ≥ 2.

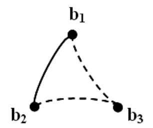
1. There are no isolated vertexes found in the BCF_2ACO because all buyers must be selected to be in the BCF_2ACO graph.
2. The BCF_2ACO graph is a Hamiltonian cycle, so a path visits each vertex exactly once and the number of edges incident to the vertex is 2.
3. Each sub coalition (m≥2) holds exactly two dotted lines to connect to the other sub coalitions.

The total number of solid lines and dotted lines used in the BCF_2ACO graph is n-1

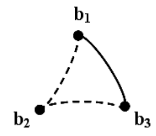
Example 1 Let B = {b_1, b_2, b_3}, the total number of BCF_2ACO graphs is eight depicted in Fig 1. If all members form a coalition to make only one group, it can be presented in four possible graphs as shown in Fig. 3(a). If all members are divided into two smaller sets, the three possibilities of all coalitions are {{b_1,b_2},{b_3}}, {{b_1,b_3},{b_2}}, and{{b_1}, {b_2,b_3}} which are represented in Fig. 3(b), Fig.3(c), and Fig. 3(d) respectively. Finally, if the whole members of B are divided into three smaller groups, {{b_1},{b_2},{b_3}}, the BCF_2ACO graph can be demonstrated in Fig. 3(e).



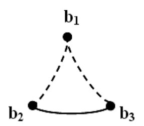
(a) Four possible graphs of coalition {b_1, b_2, b_3}



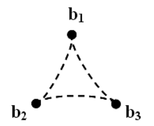
(b) Coalition $\{\{b_1, b_2\}, \{b_3\}\}$



(c) Coalition $\{\{b_1, b_3\}, \{b_2\}\}$



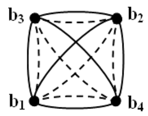
(d) Coalition $\{\{b_1\}, \{b_2, b_3\}\}$



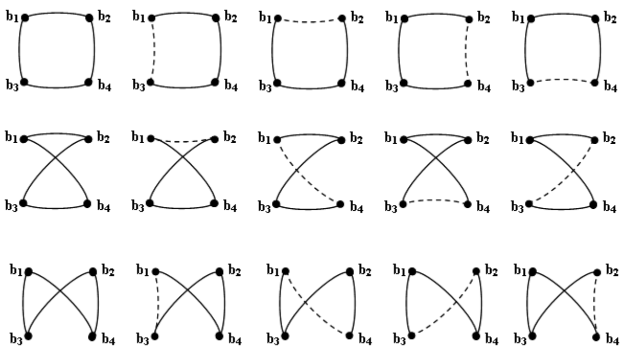
(e) Coalition $\{\{b_1\}, \{b_2\}, \{b_3\}\}$

Fig. 3 The eight possible BCF_2ACO graphs (n=3).

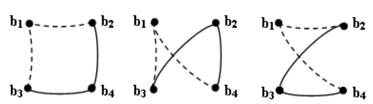
Example 2: Let B = $\{b_1, b_2, b_3, b_4\}$ be a set of buyers. Then, the total number of different BCF_2ACO graphs is forty eight as represented in Fig. 4, which are totally mapped to all coalition structures of the CS in Fig. 1. For instance, fifteen of BCF_2ACO graphs represent $\{b_1, b_2, b_3, b_4\}$.



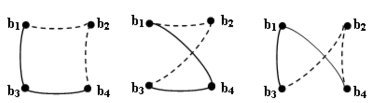
(a) Representation of all possible lines of four byers, B = $\{b_1,b_2,b_3,b_4\}$.



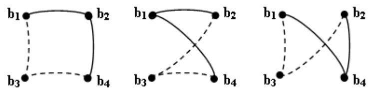
(b) One group: $\{b_1, b_2, b_3, b_4\}$



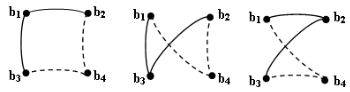
$\{\{b_1\}, \{b_2, b_3, b_4\}\}$



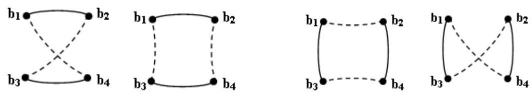
$\{\{b_2\}, \{b_1, b_3, b_4\}\}$



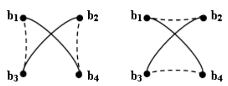
$\{\{b_3\}, \{b_1, b_2, b_4\}\}$



$\{\{b_4\}, \{b_1, b_2, b_3\}\}$

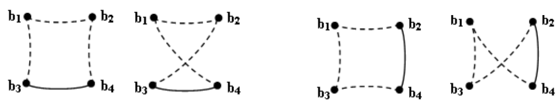


$\{\{b_1, b_2\}, \{b_3, b_4\}\}$ $\{\{b_1, b_3\}, \{b_2, b_4\}\}$

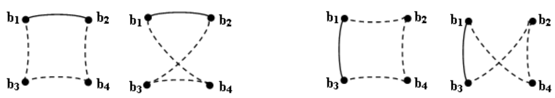


$\{\{b_1, b_4\}, \{b_2, b_3\}\}$

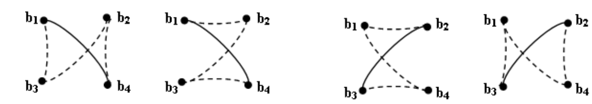
(c) Two subgroups



$\{\{b_1\}, \{b_2\}, \{b_3, b_4\}\}$ $\{\{b_1\}, \{b_3\}, \{b_2, b_4\}\}$

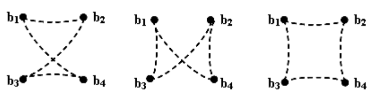


$\{\{b_3\}, \{b_4\}, \{b_1, b_2\}\}$ $\{\{b_2\}, \{b_4\}, \{b_1, b_3\}\}$



$\{\{b_2\}, \{b_3\}, \{b_1, b_4\}\}$ $\{\{b_1\}, \{b_4\}, \{b_2, b_3\}\}$

(d) Three subgroups



(e) Four subgroup $\{\{b_1\}, \{b_2\}, \{b_3\}, \{b_4\}\}$

Fig. 4 Representation of all possible BCF_2ACO graphs (Ant1) with B = $\{b_1,b_2,b_3,b_4\}$.

At the beginning of the process, all of the pheromone values of each package are initialized to the small value c, $0 < c \leq 1$. The artificial ant of the first colony, called ant m, chooses buyers for finding the best group's utility on return. After initializing the graph with a small amount of pheromones and defining each ant's starting point, several ants run for a certain iterations. The probability of the ant m to choose a buyer b_j to join with buyer b_i is $p^m_{ij_k}$, where k∈T={dotted line, solid line}, defined formally as below:

$$p^m_{ij_k} = \begin{cases} \dfrac{\left(\tau^m_{ij_k}\right)^{\alpha_1}\left(\eta_{ij_k}\right)^{\beta_1}}{\sum_i\sum_{l\in B}\sum_{d\in T}\left(\tau^m_{il_d}\right)^{\alpha_1}\left(\eta_{il_d}\right)^{\beta_1}} & \text{if } l \in \text{B and } b_l \text{ has not been selected,} \\ 0 & \text{otherwise,} \end{cases} \quad (8)$$

where $\Delta\tau^m_{ij_k}$ is the amount of pheromone laid on the line between i and j on either solid line or dotted line by an ant m defined as follows:

$$\Delta\tau^m_{ij_k} \begin{cases} 1/(U^*) & \text{if } b_i \text{ and } b_j \text{ were selected by ant m with the relation k,} \\ 0 & \text{otherwise,} \end{cases} \quad (9)$$

where U^* is the total utility of the whole buyers described in the next section. And, η_{ij_k} is given by:

$$\eta_{ij_k} = \begin{cases} 1/(D - U^{\{\{b_i\},\{b_j\}\}}) & \text{if k = 0,} \\ 1/(D - U^{\{b_i,b_j\}}) & \text{otherwise,} \end{cases} \quad (10)$$

where D is the positive constant value, and both $U^{\{\{b_i\},\{b_j\}\}}$ and $U^{\{b_i,b_j\}}$ are derived by the works of second ant colony.

B. Second Ant Colony (Ant2):

It is the creation of the coalition string and the calculation of the group's utility. During the work of the Ant1, the Ant2 works simultaneously on searching the best number of packages, which match all requests of each member in the current sub coalition. In Fig. 6, the solid line represents a package selected by the ant t. The ant t moves from starting point along the line of selected package. If the selected package is picked more than one, the ant t moves longer on the solid line. Then, the ant randomly chooses the other packages. The following packages, which are selected by the ant t, are connected with a dotted line. The probability of the ant t, at the current package i^{th}, to select packages j^{th} with n units is $p^t_{ij_n}$ formally defined in (11). Keep in mind that each package can be visited only one time during the search of the ant t.

$$p^t_{ij_n} = \begin{cases} \dfrac{(\tau_{ij_n})^{\alpha_2}(\eta_{ij_n})^{\beta_2}}{\sum_{l\in P}\sum_k(\tau_{il_k})^{\alpha_2}(\eta_{il_k})^{\beta_2}} & \text{If } l \in P, \text{ where } l \text{ the set of packages offered by all sellers which have not been selected by the ant t,} \\ 0 & \text{otherwise,} \end{cases} \quad (11)$$

where k is the number of the selected package and $\Delta\tau^t_{ij_n}$ is the intensity of the pheromone on the solid line of package j with unit n.

From example 2, if the set of four buyers are divided into two disjoint sub coalitions, which are $\{b_2,b_3\}$ and $\{b_1,b_4\}$. For purchasing the best package of products for $\{b_1,b_4\}$, the Ant2 works as follow. At the starting point, if the ant t selects two units (j=2) of P_1, the buyer b_4 receives two items of product D. The ant t keeps working until no buyer's requests left. If the ant t walks through of the path of $2P_1$-->$1P_3$, the measurement of the quality of a solution found by the ant t is calculated according to the total utility of coalitions in (1). The quantity of pheromone $\Delta\tau^t_{ij_k}$ is defined as seen in (12). Then, the ant t deposits its small value of pheromone on three spots, $2P_1$ and $1P_3$ as represented in Fig. 6(b).

$$\Delta\tau^t_{ij_k} \begin{cases} 1/U^t & \text{If package } i^{th} \text{ is selected to be together with k units of package } j^{th}, \\ 0 & \text{otherwise,} \end{cases} \quad (12)$$

And η_{ij} is given by:

$$\eta_{ij_k} = \begin{cases} \sum m_{ij} / \sum u_{ij} & \text{If some of the items in the selected package are unmatched to the buyers' requests,} \\ 1 & \text{If all items of the selected package are totally matched to the buyers' requests,} \\ 0 & \text{otherwise,} \end{cases} \quad (13)$$

where m_{ij} is the number of items of the selected packages which is matched to the buyer's requests, and u_{ij} is the total number of items in the selected packages which is unmatched to the buyers' requests.

C. The Example of the BCF_2ACO and Algorithm Revisited

The example of the BCF_2ACO is considered again in this section, and the algorithm in this paper will be described through the example as follows:

Suppose that one seller in the e-marketplace has provided three packages in the stock as shown in Table 3. During that time, there are four buyers interested to buy the goods listed in these packages. They have made some orders with the reservation prices as in Table 4.

TABLE III. THE PRICE LIST EXAMPLE

Package Number	*Products*				*Price ($)*
	A	B	C	D	
P_1	Pack of 2	-	-	-	20.0
P_2	-	Pack of 1	Pack of 1	-	22.0
P_3	Pack of 1	-	-	Pack of 2	40.0

TABLE IV. A SAMPLE OF BUYERS' RESERVATION

Buyers	*Buyer's Order (Number of item × (price $))*			
	A	B	C	D
b_1	3 x (12.0)	-	-	-
b_2	-	1 x (14.0)	-	-
b_3	-	-	1 × (10.0)	-
b_4	1 x (12.0)	-	-	2 x (14.0)

For the work of Ant1, at the beginning all pheromone values are set to a small constant c > 0. If b_3 is chosen to be the starting point, then the ant t finds the next buyers with the probability $p^t_{ij_k}$ as in (8) and (9). Suppose the Ant1 selects b_2 on the edge k = 1. It means that b_2 is chosen to be in the same group with b_3, so the current subgroup is $\{b_2, b_3\}$. The walk of an ant t can be shown in Fig. 5. (a). Then, it is the time for Ant2 on finding best packages for $\{b_2, b_3\}$. As can be seen in the table 4 and 5, the suitable package for $\{b_2, b_3\}$ is P_2, with the package price of 22. Keep in mind that this part is obtained by the Ant2, see Fig. 6 (a). Buyer b_2's reservation price for product B is 14, and buyer b_3's reservation price for product C is 10. The total utility of $\{b_2, b_3\}$, represented as $U^{\{b_2,b_3\}}$ is (14+10)-22 = 2. The selected package is put in the string of nP_m, where n is the number of selected package P_m. The coalition string created by the ant t is $\{b_2, b_3\}<1P_2>$. After that, if the process of Ant1 chooses next buyers b_1 with k = 0 by the probability $p^t_{ij_k}$ in (8) and (9). It means that buyer b_1 should not belong in $\{b_2, b_3\}$. Therefore, the Ant2 reassigns to work for b_1.Suppose that the buyer b_1 buys 3 items of product A. We can buy two sets of package P_1, so the utility of $\{b_1\}<2P_1>$ is $U^{\{b_1\}}$= (3*12)-(2*20) = -4. In this case, it is not a good way because the utility is bad. Therefore, the Ant1 can find other buyers to join with buyer b_1. If buyer b_4 is selected with k = 1 to join with buyer b_1, so the Ant2 needs to find the utility of $\{b_1, b_4\}$, represented as $U^{\{b_1,b_4\}}$. The set of buyers $\{b_1, b_4\}$ purchases two units of P_1 and one unit of P_3 represented as $<2P_11P_3>$, demonstrated in Fig. 6(b). The total utility of coalition string $\{b_1,b_4\}<2P_1P_3>$ is $U^{\{b_1,b_4\}}$ = ((3*12)+(2*12)+(2*14))-((2*20)+(1*40)) =88-80 = 8. Finally, the Ant1 completes the tour with k = 0 because there are only two subgroup created so far. Finally, the BCF_2ACO graph is represented as Fig. 5 (e). The coalition string is $\{b_2, b_3\}<1P_2>\{b_1,b_4\}<2P_11P_3>$ with the total utility $U^{\{\{b_2,b_3\},\{b_1,b_4\}\}}$ = 2+8 = 10.

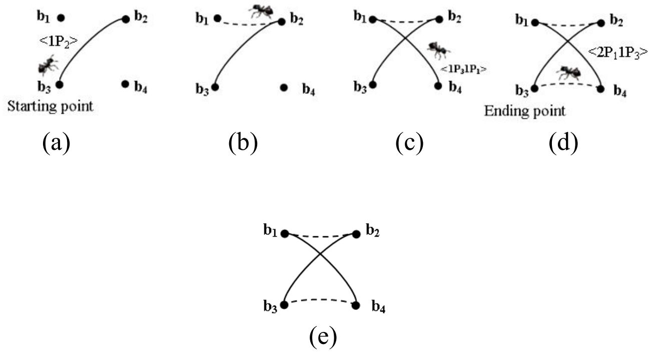
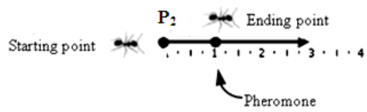
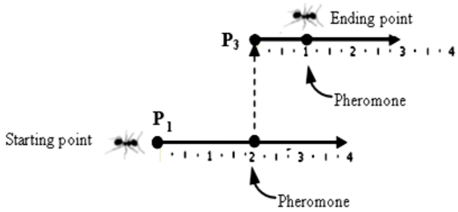


Fig. 5 Example of Ant1 creating the coaliton string: $\{b_2,b_3\}<1P_2>\{b_1,b_4\}<2P_11P_3>$.



(a) Representing the path of $<1P_2>$ for $\{b_2, b_3\}$



(b) Representing the path of $<2P_11P_3>$ for $\{b_1, b_4\}$

Fig. 6 Representing the grapht created by Ant2.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The simulation of the proposed algorithm was implemented more than 3500 lines of C++ language on a Pentium (R) D CPU 2.80 GHz, 2 GB of RAM, IBM PC. Each experiment consists of 10 runs. The parameter values for BCF_2ACO algorithm are set based on the experiments as shown in Fig 7. The parameter values of the first ant colony are $\alpha_1 = 0.5$ and $\beta_1 = 1$, and the parameter value of the second ant colony are $\alpha_2 = 1$ and $\beta_2 = 1$.

First ant colony	Second ant colony
$\alpha_1 = 0.5$	$\alpha_2 = 1$
$\beta_1 = 1$	$\beta_2 = 1$
MaxAnt1 = 100	MaxAnt2 = 300

Fig. 7 Parameters for BCF_2ACO algorithm.

In the simulation, three kinds of packages are used, which are non-bundling packages (Table 5), pure bundling packages (Table 6), and mixed bundling packages (Table 7). Moreover, two given sets of buyers are used. The first set is a group of five buyers (n = 5), demonstrated in Table 8. The second set is a group of ten buyers (n=10), shown in Table 9. As the algorithm is designed to have two artificial ant colonies, there are some situations that the algorithm works ineffectively. For example, the result derived from second ant colony is not guaranty to be an optimal result. When that happens, it could affect the efficiency of the second ant colony. So, the simulation has tried several run to get the average results. The average results are shown as follow.

TABLE V. NON-BUNDLING PACKAGES

Package Number	Products				Price ($)
	A	B	C	D	
P_1	Pack of 1	-	-	-	13.0
P_2	-	Pack of 1	-	-	11.0
P_3		-	Pack of 1	-	10.0
P_4		-	-	Pack of 1	25.0

TABLE VI. PURE BUNDLING PACKAGES

Package Number	Products				Price ($)
	A	B	C	D	
P_1	Pack of 1	Pack of 1	-	-	19.0
P_2	-	Pack of 1	Pack of 1	-	18.0
P_3	-	-	Pack of 1	Pack of 1	32.0
P_4	Pack of 1	-	Pack of 1	-	20.0
P_5	Pack of 1	-	-	Pack of 1	30.0
P_6	-	Pack of 1	-	Pack of 1	31.0

TABLE VII. MIXED BUNDLING PACKAGES

Package Number	Products				Price ($)
	A	B	C	D	
P_1	Pack of 1	-	-	-	13.0
P_2	Pack of 2	-	-	-	20.0
P_3	-	Pack of 1	-	-	11.00
P_4	-	Pack of 2	Pack of 2	-	40.0
P_5	-	-	Pack of 2	Pack of 1	40.0
P_6	-	-		Pack of 1	25.0

TABLE VIII. TEST1: BUYERS' RESERVATION (N =5)

Buyers	Buyer's Order (Number of item × (price $))			
	A	B	C	D
b_1	2 x (12.0)	-	-	-
b_2	1 x (13.0)	-	-	-
b_3	-	-	1 × (10.0)	-
b_4	-	-	1 × (10.0)	1 x (20.0)
b_5	1 x (12.0)	-	-	-

TABLE IX. TEST2: BUYERS' RESERVATION (N = 10)

Buyers	Buyer's Order (Number of item × (price $))			
	A	B	C	D
b_1	1 x (7.0)	-	-	-
b_2	-	1 x (9.0)	-	-
b_3	-	-	1 × (10.0)	-
b_4	-	1 x (11.0)	-	-
b_5	-	-	1 × (10.0)	-
b_6	1 x (12.0)	-	-	-
b_7		-	-	1 x (20.0)
b_8	1 x (13.0)	-	-	-
b_9	-	1 x (11.0)	-	-
b_{10}	1 x (7.0)	-	-	-

Table 10 summarizes the characteristic of three kinds of packages listed in Table 5-7. The average price of non-bundling packages (Table 5) is the most expensive. Any buyers who want to buy goods in this table will not gain any group's utility. Since, there is no buyer put the reservation price higher than the item price, the best utility that a group buyer can get is zero (see in Table 11 of non-bundling packages). However, when the same group of buyers is dealing with other sellers with pure bundling packages or mixed bundling packages, the group buyer gets some benefits from sellers because some buyers can join their requests together to buy bigger packages. In most cases, every group of buyers formed by BCF_2ACO algorithm is able to get the group utility. Due the design of BCF_2ACO algorithm, the algorithm is able to form a group buyer by isolating some buyers, which their requests are able to decrease or destroy the group buying. For instance, the BCF_2ACO algorithm forms a group buying of 10 buyers in Table 9. The maximum number of buyers who can get the items is six for Table 6 and seven for Table 7. There are two reasons that some buyers cannot receive their goods. First, buyers have placed their requests with bad reservation's prices. The other reason is that the buyer requests cannot be assembled with other requests of buyers to purchase any package at the cheaper price.

As stated above, the BCF_2ACO algorithm is designed to isolate the poor quality of buyers out of the group. So, it can be seen that there are some buyers with bad reservation prices are removed. The experimental results received by the BCF_2ACO algorithm are higher than the results received by the GroupPackageString scheme. For example, buyer b_1, b_2, b_7, and b_{10} of test 2 have made bad reservation prices on their requests. The BCF_2ACO algorithm isolates these buyers into new subgroups. When these unqualified buyers are out of the main group buying, then the group formation of six buyers can be form. The utility earned by the algorithm is 6.94$ (see Table 11 of pure bundling packages), while the GroupPackageString scheme form the whole group of 10 buyers with the utility of 1.61$. Also, the efficiency of the BCF_2ACO algorithm over the GroupPackageString scheme can be seen when buyers are dealing with the seller of mixed bundling packages. The GroupPackageString scheme fails to form a group buying of n=10 because the best value earned from the GroupPackageString scheme is poor (negative cost, -

6.41$), while the BCF_2ACO algorithm is able to forms the group buying of six buyers with the utility of 6.32$. The average total utility earned by the BCF_2ACO algorithm is acceptable. It is about 83.17% of the best value.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, the coalition structure is considered for forming a buying group. The algorithm is proposed for forming a buyer coalition through the use of ant colony optimization technique, called BCF_2ACO algorithm. The ants apply a stochastic greedy rule to construct BCF_2ACO graph over the disjoint sets of buyers by depositing pheromone after moving through a path and updating pheromone value associate with good or promising solutions thought the lines of the path. The central idea for the proposed algorithm is to form a buyer coalition where a whole group of buyers can be partitioned into smaller sub-groups to get the group's total utility more efficiently than they could accomplish in the whole. The solution quality of the BCF_2ACO algorithm is demonstrated by comparing with the previous genetic algorithm technique called GroupPackageString scheme. From the experimental results, it is observed that in most cases the proposed algorithm performs better in finding buyer's utility. In future work, the algorithm is employed for different assumptions regarding multiple objectives and coalition values.

TABLE X. CHARACTERISTIC OF BUNDLING PACKAGES AND BUYERS REQUESTS

Type of bundling packages offered by sellers	Number of packages	Average price per item of sellers	Average number of items/package	Average price per item of buyers / Average price per item of sellers	
				Test1 (n=5)	Test2 (n=10)
NON-BUNDLING PACKAGES	4	14.75	1	12.7/14.75 = 0.86	11/14.75 = 0.75
PURE BUNDLING PACKAGES	6	12.50	2	12.7/12.50=1.02	11/12.50=0.88
MIXED BUNDLING PACKAGES	6	12.41	2	12.7/12.41=1.02	11/12.41=0.89

TABLE XI. SIMULATION RESULTS DERIVED FROM DIFFERENT ALGORITHMS

Type of bundling packages offered by Sellers	Number of buyers (n)	BCF_2ACO algorithm				GroupPackageString scheme		
		Best value ($)	Average total utility ($) (10 runs)	Max Number of buyers who can get the items	Average number of coaltions	Best value ($)	Average total utility ($) (10 runs)	Max Number of buyers who can get the items
NON-BUNDLING PACKAGES (4 PACKAGES)	5	0	0 (100%)	2 (40%)	3.56	-8.00	-12.15	0
	10	0	0 (100%)	5 (50%)	3.12	-20	-31.41	0
PURE BUNDLING PACKAGES (6 PACKAGES)	5	7.00	5.61 (80.14%)	4 (80%)	1.97	0.00	-5.47	5 (100%)
	10	10.00	6.94(69.40%)	6 (60%)	3.17	4.00	1.61	10 (100%)
MIXED BUNDLING PACKAGES (6 PACKAGES)	5	9.00	7.11(79.00%)	5 (100%)	1.23	9.00	7.97	5 (100%)
	10	9.00	6.32(70.22%)	7 (70%)	3.13	-3.0	-6.41	0%
		Average	83.17%					

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