Auction-based Task Allocation Scheme for Dynamic Coalition Formations in Limited Robotic Swarms with Heterogeneous Capabilities

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***Abstract*— Task allocation is one of the main issues to be addressed in the domain of multi-robot systems, in which it is determined which robot(s) should execute which task(s) so that overall system goal is achieved. Such collective decision making process is of great significance during complex task execution by swarm of simple robots with heterogeneous capabilities. This work targets the issue of coalition formations in a limited swarm of robots to perform a task requiring multiple single-task robots (ST-MR-IA) depending upon their heterogeneous capability conditions. Capabilities of individual robots may vary to different certain levels in a dynamic environment during task execution which can further affect the coalition formed to execute a specific complex task requiring certain level of collective/group capability. This study aims to suggest an algorithm for task allocations through auction mechanism to form a new or modify a coalition underway, where individual robots may gain or lose their task capabilities at certain time instants. Effectiveness of proposed algorithm in terms of task-execution time and utility of coalitions is analyzed through simulations.**

Keywords- ***Multi-Robot Task Allocation; Multi-Robot Systems; Multi-Robot Coordination; Swarm Robotics;***

I. INTRODUCTION

Multi-robot coordination has been acknowledged with greater attention in recent days, as developments in the field of robotics are on rise. Such coordination is much more significant in such situations when a complex task cannot be accomplished by a single robot. Multi-robot systems provide several advantages rather than using single-robot systems, like robustness, flexibility and efficiency. Such benefits can be achieved through effective coordination by multi-robot task allocation (MRTA) [1-3].

Gerkey [4] proposed a clear definition of MRTA as: there are given *m* robots and *n* weighted tasks. Each robot is capable of executing one task and each task requires one robot. The objective is to assign robots to tasks in such a way so that maximized overall performance can be achieved. There are several approaches to deal with MRTA such as behavior based approach e.g. [6-9], swarm intelligence based approach [10, 11], market-based approach [12-15] and the approaches based on linear programming.

Task allocation algorithms presented in this work are distributed because robots do not know all of the tasks at beginning. Due to not having any prior information about the tasks, the information of the task under auction and robot state is used to calculate the cost. Therefore, algorithm can be used in dynamic situations. The quality of solution depends on communication range because inter-robot communication is used to allocate different tasks to robots to form coalitions and this has been a limitation for such multi-robot systems.

We can see the proposed work in two phases. The first phase deals with newly coalition formations made which is mostly inspired from the work of Guererro [29] and Antidio Viguria [27]. The second phase which is main contribution of this work deals with time-varying capabilities of coalition members. We assume the capabilities of coalition members including coalition leader decreases at certain level at specific stage of task underway and task performance is also decreased. Rather than continuing the task execution with such decreases capabilities, reallocations of coalition members can be feasible solution because there might be the other task which can be done with new capability values and there can robots in other coalitions with higher capabilities but not useful for that specific coalition.

This paper is organized as follows; section-II details the related work focusing on the issue of multi-robot task allocation (MRTA), different approaches to deal MRTA and multi-robot coalition formations. We illustrate the problem in section-III with specific assumptions related to robots, tasks and environment. Section-IV consists of proposed methodology and section-V provides the simulation details and results. Section-VI provides conclusion and outlines potential avenues for future work.

II. RELATED WORKS

Nowadays, there are different approaches to deal with multi-robot task allocation (MRTA) problems like behavior-based approach, swarm-intelligence approach inspired by insect colonies behavior and market-based approach where individual robots bid for the task announced depending upon their reward and cost functions.

To discuss the above mentioned approaches towards MRTA issue, ALLIANCE [6] represents the "behavior based approach". It has been the most investigated approach in the multi-robot task allocation problem. Seuken [9] used partially observable Markov decision process (MA-POMDPs) for allocations on the cost of high time complexity.

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On the other hand side, based on swarm intelligence, Jiang [10] proposed ACO algorithm based multi-robot task allocation method. In [11], Yu also used ACO algorithm for a centralized planning approach, where the distributional effects of the ant colony algorithm are improved through local search strategy.

The most popular way for solving the multi-robot task allocation (MRTA) problems is the "market-based mechanism". The common feature in market-based allocation mechanisms is an auction protocol to coordinate tasks between different robots as investigated by various works [12, 13, 17, 19]. When a task to be executed, is announced, each capable robot computes bids, based on their expected profit for the tasks and the robots with the lowest cost-bid are rewarded with that announced task.

Stentz and Dias [14] utilized a market-based scheme to coordinate multiple robots for ST-MR cooperative task completion that introduced the application of market mechanisms to intra-team robot coordination. Murdoch [17] was presented by Gerkey is a market-based system. Dias [20] proposed a framework for distributed control in multi-robot systems. Kalra [15] proposed Hoplites, but without global optimal search. A dynamic task allocation method was proposed by Zu [21] which reduced communication traffic by shortening task completion time.

Guerrero [29] presented MRTA method partially inspired on auction and thresholds-based methods, to allocate tasks with priorities in a team of heterogeneous robots. Dong-Hyun Lee [22] also presented a market-based framework for task allocation based on task preferences. The utility of a robot is calculated using the bid elements and their weighted preferences. Many of the above stated works deal with tasks which require only single robot with capability performing single task. This is also called ST-SR-IA category of MRTA, according to taxonomy presented by Gerkey and Mataric [4].

Rather than ST-SR-IA, we are interested in ST-MR-IA problem. ST-MR-IA problem is significantly harder and is also referred as "coalition formations" and NP-hard optimization problem like other MRTA categories except ST-SR-IA [4]. Very recently, a comprehensive taxonomy iTax by Korsah [5] also discusses the MRTA categorization in terms of dependencies with existing mathematical models from combinatorial optimization and operations research.

Vig Lovekesh [30] presented market-based multi-robot coalition formation by a framework RACHNA, a novel architecture for distributed task allocation scheme based on the multi-unit combinatorial auction problem. Vig Lovekesh [31] presented a method derived from multi-agent systems. In this method, the complexity of distributed computing is $O(|R|^k)$ and complexity of centralized computing is $O(|R|^{k+1})$. Antidio Viguria [27] discussed the significance of market-based task allocation algorithm for initial robotic formations. They presented a probabilistic analysis approach for analyzing market-based algorithms applied to initial formation problem. A market-based multi-robot task planning framework, ASyMTRe is proposed by [32]. It also has a distributed version as ASyMTRe-D. Their time complexity is O(|R|!).

Guerrero [29] presented multi-robot coalition formation in real-time scenarios. It is a new model to predict the time to execute a task, where the robots needed to carry out a task before a deadline. By learning the physical interference, coalition utility is calculated from the past experience using online Support vector Regression method (SVR).

This work aims to suggest auction-based mechanism for multi-robot coalition formations with heterogeneous capacities to deal with ST-MR tasks in a dynamic scenario, where a complex task is being executed by multiple robot coalitions (teams). Furthermore, it is considered that capabilities of each robot in a coalition is decreased as it is consumed to execute a given tasks. There are varieties of applications where we can see that resources are lessened as task requirements are fulfilled or task is executed. This study suggests an auctioned-based algorithm to enable multiple coalition leaders to re-adjust their coalitions in case collective capacity of coalition is reduced below task work load. The algorithm provides a way to swap robots among coalitions through auction mechanism to increase overall system performance.

III. Problem Definition

This section describes the basic definitions and general multi-robot problem to be solved with some certain assumptions regarding environment, tasks and robots.

We assume that robots can fully communicate with each other, task is independent, instantaneous assignment and delay of task will cause cost. Task is independent, i.e. task should be carried out without dependency on other tasks. When a robot is executing a task, here is no need to coordinate with other tasks but a weakly dependency on time should be allowed, especially when a multi-robot task is decomposed into several subtasks.

In market-based task allocation, the robots with their capabilities and the tasks with their requirements are required to define explicitly.

A. Robots and Capability Vector

Let, $R = \{r_1, r_2. \ . \ . \ , r_n\}$ the set of n robots. Based on hardware resources, robots may have numerous capabilities with different characteristics. The capability matrix of a the i^{th} robot, r_i, $i \in \{1, 2, \ldots n\}$, cap_{ik} , $k \in \{1,2,\ldots., m\}$, is given as

$$cap_{ik} = \begin{bmatrix} q_{ik} & c_{ik} \end{bmatrix}^T \quad \ldots (1)$$

where n and m are number of robots and number of capabilities of each robot, respectively. On the other hand side, q_{ik} and c_{ik} represents capability quality and capability cost, respectively. A robot continuously monitors its capabilities during task executions. Formal definition of the *robot capability matrix* can be given as

$$R_i^{cap} = [Cap_{i1} \quad Cap_{i2} \quad \ldots \quad Cap_{im}] \quad \ldots (2)$$

B. Tasks and Requirement Vector

Let $T = \{t_1, \ . \ . \ . \ , t_a\}$ be a set of 'a' compound tasks. Every task t_j has its own requirements to be fulfilled so that it can be performed. The *task requirement matrix* consists of required capabilities and required quality of such capabilities of robot so that the task can be accomplished. Formally, k^{th} requirement vector of j^{th} task is given as

$$req_{jk} = \begin{bmatrix} h_{jk} & w_{jk} \end{bmatrix}^T \quad \ldots (3)$$

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Where, h_{jk} ($h_{jk} \in \{0,1\}$) represents the requirement of the k^{th} capability. Formal definition of the *task requirement matrix* can be given as

$$T_j^{req} = [req_{j1} \quad req_{j2} \quad \dots \quad req_{jm}] \qquad \dots (4)$$

Here, it is worth noting that every t_j, $1 \le j \le a$, is itself multi-robot task which means it will be executed by multi-robot coalition.

C. Objective function

- When a task t_j is executed, the corresponding robot will receive a utility value
$$U(t_j) = r_value, \qquad r_value \in R_0^+ \qquad \dots (5)$$
- Meanwhile, every task t_j is executed by robot r_i causes cost value
$$C(r_i, t_j) = c_value, \qquad c_value \in R_0^+ \qquad \dots (6)$$
- The net gain of robot r_i can be calculated by subtracting the cost value $C(r_i,t_j)$ from utility value $U(t_j)$.
$$G(r_i, t_j) = U(t_j) - C(r_i, t_j) \qquad \dots (7)$$
- A robot pursuits to maximized net gain value $G(r_i,t_j)$ when going to execute the given task. The goal of MRTA method is to find the optimum assignment $G^* \in G$ that maximizes the net gains, that is
$$G^* = \arg\max_{t_j \in T, r_i \in R} \left(G(r_i, t_j) \right)$$

D. Task workload vs coalition capacity

- Each task t_j has the characteristics of workload ($taskWorkload_j$), which is the amount of work needed to finish it, $taskWorkload_j \in R^+$
- Each robot r_i has individual work capacity associated with each task t_j ($robotCapacity_{i,j}$) that represents the amount of work that the robot can process per time unit, denoted as $robotCapacity_{i,j} \in R^+$
- A group of robots termed as coalition to take charge of a task t_j, has a collective work capacity as
$$coalitionCapacity_{c,j} = \sum_{1 \le i \le n_g} robotCapacity_{i,j} \qquad \dots (8)$$

where n_g represents total number of robots in the specific coalition. In [30], *coalitionCapacity* is also calculated including the term "*I*" which represents physical interference among robots while performing a task with deadlines. Therefore, the time to fulfill a task mainly depends on the number of robots of the coalition assigned to it, the $robotCapacity_{i,j}$ of each of them and the physical interference *"I"* among the robots. In this work, the factor of interference is ignored because deadlines for task performance are not being targeted.

IV. AUCTION-BASED TASK ALLOCATION ALGORITHM

The task allocation mechanism includes coalition formation for specific number of multi-robot tasks, continuous monitoring of capabilities of individual robots in a coalition, reallocating the tasks or coalitions for those robots whose capability levels are changed due to specific reason e.g. reduced energy level, gain specific capability to perform more difficult task while performing simple task.

We can divide the proposed work in two phases. The first phase deals with new coalition formations, which is mostly inspired from the work of Guerrero [12] and Antidio Viguria[10].

The second phase which is main contribution of this work deals with time-varying capabilities of coalition members and reallocations of coalitions for such coalition members in case the current coalition capacity is decreased than the required task workload at specific time instance. We assume that the capabilities of coalition members including coalition leader decreases at certain level at specific stage of task underway and task performance is also decreased. Rather than continuing the task execution with such insufficient coalition capacity to perform task, reallocations of coalition members can be feasible solution because there might be the other tasks which can be done with current capacity values and there can robots in other coalitions with higher and extra capacity values for that specific coalition.

Description: Tasks can be announced by different means like human-operator, an autonomous computer or robots themselves. There is no limitation on auctioneers, there can be multiple MR tasks being executed by different coalitions in parallel. Such task allocation process illustrated in fig. 1, is also suggested in [10].

Phase-I: *Initial Coalition Formation*

Initially, multiple robots and multiple tasks are spread cross the working space, randomly. Every robot wanders randomly through the environment. Once the task is announced in specific region and robot receives the announced task, it compares the values in *robot_capability_vector* and *task_requirement_vector*, *cost_value* is calculated and a bid message is sent back to auctioneer.

The auctioneer evaluates the received bids and calculates the *Net_gain_value* by subtracting the *cost_value* from *task_utility*. The announced task is allocated to robot with best bid, through an allocation message.

When a robot is selected as leader for specific task *t,* it evaluates the work needed to perform it. As the given task is multi-robot task in nature, for this purpose, leader robot requires coalition members. It will create a work group by making auctions to nearby robots. Leader robot uses auctioned-base mechanism to form a coalition by recruiting the coalition members based on their individual *robotCapacity* so that it can compete with requirement of *taskWorkload*.

Phase-II: Coalition Re-adjustment

In this phase, which is core work of this study, we observe that there are multiple coalitions have been formed for multiple tasks in a given working space. Each coalition has a coalition leader robot that monitors the progress of the task workload and coalition capacity in continuously. During execution of each portion of task workload, *coalitionCapacity* is updated by the summation of individual robot capacities according to eq. (8). The leftover task workload is compared with the available capacity of the coalition and coalition award is also calculated in parallel,

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so that performance of coalition in terms of coalition efficiency can be measured.

Algorithm 1: Coalition Readjustment Algorithm

Input: - Coalition C_j with assigned taskWorkload$_j$
- CoalitionSize$_j$, robotCapacity$_i$ and individual contribution to task, contribute$_i$
- List R_L of leader robots of each neighboring coalition C_A

Output: Maximized coalition award

1. time$_{init}$ ← time
2. coalitionAward$_j$ ← 0
3. coalitionCap$_j$← 0
4. **for** all $R_i \in C_j$ **do**
5. coalitionCap$_j$ ← coalitionCap$_j$ + capacity$_i$
6. **end for**
7. **while** taskWorkload > 0 **do**
8. **If** coalitionCap$_j \geq$ taskWorkload$_j$ **then**
9. **for** all $R_i \in C_j$ **do**
10. execute task
11. robotCapacity$_i$ ← robotCapacity$_i$ – contribute$_i$
12. taskWorkload ← taskWorkload – contribute$_i$
13. coalitionAward ←coalitionAward+ ΔtaskWorkload
14. **end for**
15. **else**
16. Go for auction with R_L to swap member
17. **end if**
18. **end while**
19. Dissolve coalition

As the task workload become higher than the available coalition capacity, leader robot or goes for negotiations with other coalitions in neighborhood. The coalition leader calculates the load-factor for each coalition member. The coalition member having individual capacity less than the load factor is auctioned to be swapped by another new coalition member with higher individual capacity, which can be sufficient to raise the coalition capacity more than required task workload.

Algorithm 2 describes the procedure for intra-coalition leaders to swap coalition members to increase the coalition capacity to deal with assigned task workload.

Algorithm 2: Intra-Coalition Leaders Auction-based Algorithm

Input: Coalition C_j with assigned taskWorkload$_j$
List R_L of leader robots of each coalition C_A
Output: coalition members to swap

1. **for** each R_i **do**
2. compute load_factor$_i$ ← taskWorkload /coalitionCap$_j$
3. **if** load_factor$_i$ < capacity$_i$ **then**
4. send R_i and load_factor$_i$ to R_L
5. wait for swap-member
6. **if** swap possible **then**
7. Update coalition C_j
8. Continue
9. **end**
10. **end if**
11. **end for**

V. Results and Analysis

A. Simulation Platform

Initially, simulations are made in multi-agent discrete-event based simulator. Working environment is a grid of specific number of patches as ground field where multiple robots are wandering and searching for the target object to transport.

Till now, in this simulation, from searching phase to team to team-recruitment process is implemented where 60 × 40 grid is considered as working field for round-shape robots, object-points in red color and goal location in purple color in right upper corner.

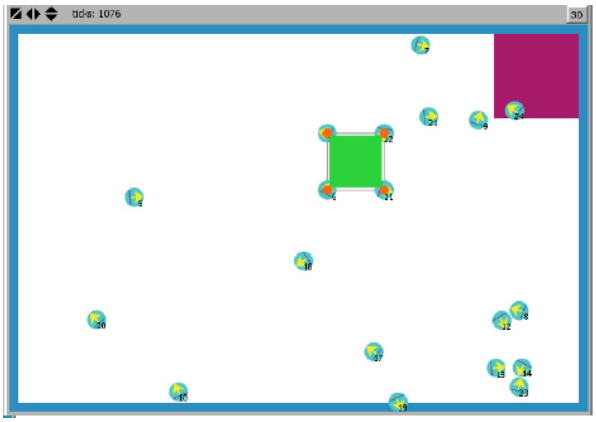


Figure 1. An initial setup of simulation and initial coalition formation

B. Results of Simulations and Discussions

To validate the algorithm, we use two different configurations based on total capacity available on each robot and amount of contribution to assigned task for each robot.

1) Homogenous capacities with hetergenous contributions: In this configuration, a coalition of 4 robots is formed to deal with task workload of 47 units and total coalition capacity of 60 units, where all robots have the same capacities (15 units) but each robot within in the coalition is not necessarily to contribute the same amount

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of work as discussed in case-1. Heterogeneous contributoins are set as (3, 1, 2, 4) for robots (1, 2, 3, 4) respectively. Based on utilization of resources, Fig. 3 shows that task workload and coalition's capacity, both are decreased as time proceeds, while the avalaible coalition capacity remains higher than the required task workload. In this case, too, there is no need to any re-adjust the original coalition formed, as coalition's capacity is never below the task workload. When task workload reaches to zero (completed), coalition capacity is still in positive value (13).

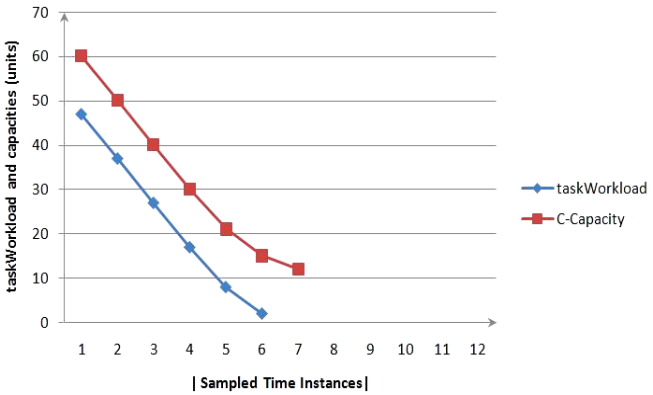


Figure 2. Performance comparison of algorithm when Coalition Capacity is higher than assigned Task Workload

Individual capacities of coalition member robots can also be observed to be utilized differently to each other, due to heterogeneous contributions to task workload.

2) Hetergeneous capacities with hetergeneous contributions: In this configuration, a coalition of 4 robots is formed to deal with task workload of 42 units and total coalition capacity of 43 units, where all robots have the heterogenous capacities as (16, 8, 5, 14) units heterogeneous contributions are set as (3, 1, 2, 4) for robots (1, 2, 3, 4) respectively. Based on utilization of resources, Fig. 4 shows that task workload and coalition's capacity, both are decreased as time proceeds, while the avalaible coalition capacity remains higher than the required task workload. Inititally, it is seen that coalition capacity is sufficient for required task work load, but at time instance 3, we consider there is abrupt change in task workload or coalition capacity, therefore coalition capacity becomes lower than the required task workload. This trend continues till the end total utilization of resources in terms of colaition capacity. Finally, we can see the coalition could not complete the assigned task workload. At time instance 9, coalition capacity reaches to zero while task workload is still needs to execute 7 units more which means coalition failed to execute the given task perfectly.

To overcome this situation, each coalition is enabled to re-adjust itself whenever it is observed that the coalition capacity is not sufficient enough to meet the required task workload. By employing the auction-based coalition re-adjustment algorithm (discussed in section- IV), the coalition leader can deal with such sudden changes in task workload as discussed above. The coalition leader can negotiate with other coalition leaders to swap its member having lowest capacity (using the *load-factor* component) by a higher capacity holder coalition member. The success of such negotiation to swap a coalition member is also subject to the net gain value of coalition member in new coalition. This is ensured that the coalition members being swapped will be sufficient to maintain the coalition capacities to deal with assigned workloads.

Using the same configuration parameters of the case represented above (and in fig. 3), fig. 4 represents the results obtained by employing the coalition re-adjustment algorithm. Initially, task execution proceeds with task workload of 42 units with coalition capacity of 43 (higher than the required). As changes occur in the task workload (as in this case) or coalition capacity like in fig. 5, the coalition capacity (23 units) at time instance 3 drops below the task workload (30 units) due to individual capacity of Robot-3, the coalition leader goes for swapping the coalition member with higher individual capacity to strengthen the coalition capacity.

After successful negotiations, coalition leader successfully removed the Robot-3 from coalition and added Robot-5 as new coalition member with initial individual capacity of 10 units, which causes to coalition capacity (32) higher than the task workload (30) at time instance 3. Later on, coalition capacity remains sufficient to execute the task workload. When task workload reaches to zero, coalition capacity still has 2 units extra.

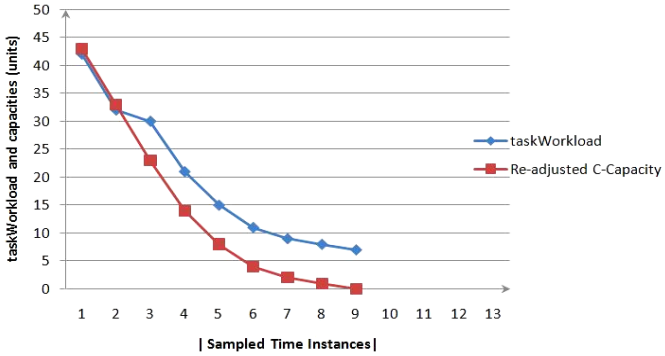


Figure 3. Non- Re-adjusted Coalition - (Heterogeneous capacities and Heterogeneous contributions).

Finally, we can say that the proposed algorithm for coalition re-adjustment algorithm works fine in a situation where task workload or coalition capacity is changed due to the dynamic nature of the environment. Compared with all stated related works, such heterogeneous capacities are not dealt in this way to avoid dynamic interruptions through environment or robot failures during the task execution by multi-robot coalition and this can be considered the main contribution of this work.

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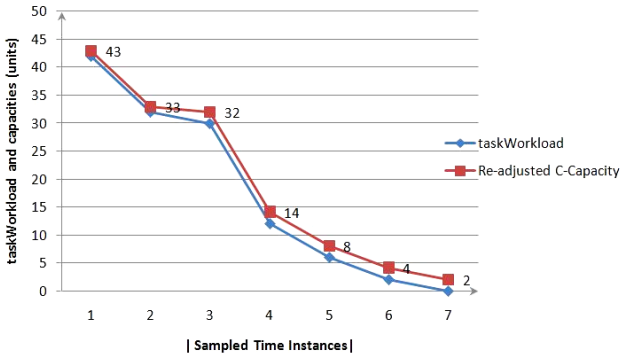


Figure 4. Re-adjusted Coalition - (Heterogeneous capacities and Heterogeneous contributions)

VI. Conclusion and Future Work

This work aims to present auction-based task allocation mechanism for multi-robot coalition formations in such a dynamic scenario where coalition members experience decreased capabilities or sudden increase in given task workload while performing a complex task with specific requirements. In such situations, rather than continuing the task execution with available originally calculated collective coalition capacity by individual robot capacities, it is suggested to re-adjust the coalition by swapping a coalition member with lowest load factor with higher individual capacity from other coalition. For such purpose intra-coalition leaders negotiations happen.

This paper presents a work in progress that has challenging features to introduce and there is a lot to do suggest mathematical model and analysis with more details with implementations for real world related problems, as a future work.

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