

GAIA: A Dynamic Crowdmapping Framework based on Hedonic Coalition Formation Games

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Abstract—Crowdsourcing has been widely employed to collect information, either at regional or global scales, about different phenomena, by engaging user communities, in order to complement or even substitute other specialized and expensive means and sources of data. In such a setting, the design of crowdsourcing models that can jointly provide appropriate rewards to the users in order to incentivize them to participate in the crowdsourcing process, while at the same time provide the necessary information to potentially various tasks (mapped to different geographical areas) announced by a requester is of high research and practical importance. In this paper, a novel dynamic crowdmapping framework is introduced, to enable the users autonomously select the geographical area, and thus corresponding task, where they will contribute their available information based on a hedonic coalition formation game. Based on the proposed hedonic coalition formation game, the requester also allocates appropriate rewards to the users considering their quality and quantity of information. The existence of a Nash-stable and individual-stable coalition formation is proven and a hedonic coalition formation algorithm is introduced to determine the stable coalition formation. The performance evaluation of the proposed framework is achieved via modeling and simulation.

Index Terms—Hedonic Games, Social Networks, Influencers, Social Activity, Game Theory.

I. INTRODUCTION

Crowdsourcing paradigm emerges as a distributed problem-solving model, where a requester, i.e., crowdsourcing platforms, such as Google Maps, Amazon Mechanical Turk, out-sources tasks to the users by providing appropriate incentives. Among, the key challenges are the appropriate design of incentive mechanisms in order to motivate participants to provide useful information [1]. In this paper, we introduce GAIA, a dynamic crowdmapping framework based on the theory of hedonic coalition formation games. Crowdmapping is a special type of crowdsourcing enabling the creation of a digital map to study the geographical spread of a phenomenon, e.g., elections, natural disasters, traffic, etc. The proposed framework jointly enables the users' autonomous decision-making to support a crowdmapping task among the multiple ones submitted by the requester, and the crowdmapping manager to provide appropriate rewards to the users.

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A. Related Work

Crowdsourcing has been thoroughly studied in the recent literature, mainly from the perspective of designing appropriate reward mechanisms to incentivize the users to provide valuable information. In [2], a dynamic payment method is introduced in order to allocate rewards to the users, and an auction - screening method is adopted to select the users who will contribute to each task submitted by the requester. A Stackelberg game-theoretic model is analyzed in [3], where the requester (leader) announces the rewards assigned to each task, and the users (followers) decide their participation (or not) in a specific task. A contract-theoretic model is proposed in [4], where an employer-employee relationship is established between the requester and the users. The requester provides personalized rewards to each user based on the quantity and quality of the provided information. Focusing on the quality of the user's provided information, a coalitional game-theoretic framework is introduced in [5] towards improving the participation of truthful users by providing higher rewards to them. Following a similar philosophy, the authors in [6] exploit the users' reputation and reliability, as it is derived from a participatory crowdsourcing environment and based on those criteria, they select lead users for each requested task.

The users' quality and quantity of information however are characterized by great stochasticity in a realistic crowdsourcing environment, thus, the authors in [7] adopt a moral hazard contract-theoretic model to determine the optimal rewards provided by the requester to the users. This model has been extended in [8] considering multiple requesters competing over the users' valuable information. The theory of the generalized Colonel Blotto game is adopted to determine the optimal rewards allocated by each requester to each user in order to recruit the latter one. The authors in [9] focus their study on maximizing the social welfare in the crowdsourcing process by introducing an optimization algorithm for the users' tasks selection.

B. Contributions and Outline

Apparently, the design of crowdsourcing models that can jointly provide appropriate rewards to the users in order to incentivize them to participate in the crowdsourcing process and at the same time provide necessary information for each

task announced by the requester, remains an open research problem. In this paper, we strive to jointly tackle these issues by introducing GAIA, a novel dynamic crowdmapping framework, based on the theory of hedonic coalition formation games. The main contributions of this article are as follows:

- 1) A novel crowdmapping model, named GAIA, is introduced, where the requester announces different crowdmapping tasks at each geographical area and provides rewards to the users per area accounting for the quality and quantity of their provided information. The novel concept of an area's criticality is introduced, considering the information availability and the uncertainty of the information integrity per geographical area, where a crowdmapping task is requested.
- 2) The users select in an autonomous manner the geographical area, where they contribute their information, in order to achieve the maximum possible payoff during the crowdmapping process, taking into account the choices of the rest of the users, which have an impact on their experienced payoff. The selection of a geographical area, i.e., coalition formation, is performed based on the theory of hedonic coalition formation games. The existence of a Nash-stable and individual-stable coalition formation is proven and a hedonic coalition formation algorithm is introduced to determine the stable coalition formation.
- 3) The proposed model enables the requester to intelligently guide the users to contribute to tasks of higher priority by appropriately managing the allocated rewards and at the same time considering the users' quality and quantity of the provided information.

The remainder of this paper is organized as follows. First, we introduce the proposed crowdmapping model in Section II. Then, the coalition formation problem is described in Section III, and the Nash-stable and individual-stable coalition formation solution along with a distributed algorithm that converges to this solution, are presented in Section IV. The performance evaluation of the proposed framework is conducted via modeling and simulation in Section V, while Section VI concludes the paper.

II. CROWDMAPPING MODEL

Crowdmapping is a special case of crowdsourcing, where the requester aims at collecting information from the users in order to create a digital map to study the geographical spread of a phenomenon, such as elections, traffic, natural disasters, etc. The requester organizes the overall area of interest into smaller geographical areas, and announces a crowdmapping task per area, while allocating an overall reward per area (i.e. task) to be shared among the users who will contribute to this task. The users are incentivized by the potential reward that they will receive in order to share their information from the geographical area that they belong to, or are willing to travel to in order to collect and report information.

We consider the set of geographical areas $\mathcal{M} = \{1, \dots, m, \dots, M\}$ and the set of users $\mathcal{J} = \{1, \dots, j, \dots, J\}$. Each user j can report different types of information, such

as text (e.g., tweets, reviews), photos, and videos, and let us denote by t_j the length of the text, p_j the number of photos and v_j the number of videos, respectively. Thus, the total amount of information provided by a user j to a selected geographical area m is defined as follows:

$$I_j(t_j, p_j, v_j) = w_t t_j + w_p p_j + w_v v_j \quad (1)$$

where $w_t < w_p < w_v$ considering that the videos can provide richer information and $w_t + w_p + w_v = 1$.

The users, as part of the proposed model and framework, can select the geographical area where they will contribute their information, and they practically create a coalition $\mathcal{S}_m$ with the other users who have also selected the same area m to provide their information. Thus, each area is characterized by a virtual value $v(\mathcal{S}_m) = \sum_{j \in \mathcal{S}_m} I_j$ that depends on the overall amount of information provided in the area m by the users' coalition $\mathcal{S}_m$. Based on the area's value and the quality and quantity of information provided by each user, the requester allocates the rewards to the users following the principles of proportional fairness, as follows:

$$\frac{I_j}{v(\mathcal{S}_m)} \cdot r_m = \frac{I_j}{\sum_{j \in \mathcal{S}_m} I_j} \cdot r_m \quad (2)$$

where $r_m[\$]$ is the total available reward assigned to the geographical area m for the crowdmapping purposes.

The provided information by the user j in area m at a time slot t is characterized by an uncertainty of the information integrity $UI_{j,m}^t \in [0, 1]$, given that this information is not a priori known if it will be useful for the requester. Thus, the information availability in an area m that is observed by the users not contributing in this area is defined as

$$IA_{\mathcal{M}' \rightarrow m}^t = \sum_{i \in \mathcal{M}'} [UI_{i,m}^t \cdot \frac{\sum_{j \in \mathcal{S}_m} I_j}{\sum_{m=1}^M \sum_{j \in \mathcal{S}_m} I_j}] \quad (3)$$

where $\mathcal{M}' = M \setminus \{m\}$ is the set of the rest $M - 1$ areas that maintain the information of $IA_{\mathcal{M}' \rightarrow m}^t$. The users can exploit this factor to identify areas, where either few users contribute information (thus, they have a higher chance to receive a higher reward), or the requester has lower demand in collecting information, thus, it allocates in advance a lower reward in that area for the corresponding crowdmapping task.

In the crowdmapping process, more recently collected information by the requester has a higher impact on the study of the geographical spread of a phenomenon. Thus, the freshness fading function is used to weigh more the most recently received information, as follows:

$$\theta_\tau = z^{t-\tau} \quad (4)$$

where t is the overall timeslots that have passed studying the spread of the phenomenon and τ denotes the index of the timeslot. Based on the freshness fading function, as presented

in Eq. 4, we can determine the fading-aware uncertainty of information integrity, as follows:

$$UI_{\mathcal{M}' \rightarrow m} = \frac{\sum_{\forall j \in \mathcal{M}'} \sum_{\tau=1}^t \theta_{\tau} UI_{j,m}^{\tau}}{\sum_{\tau=1}^t \theta_{\tau}} \quad (5)$$

and the corresponding fading-aware information availability.

$$IA_{\mathcal{M}' \rightarrow m} = \frac{\sum_{\tau=1}^t \theta_{\tau} IA_{\mathcal{M}' \rightarrow m}^{\tau}}{\sum_{\tau=1}^t \theta_{\tau}} \quad (6)$$

The physical meaning of the fading-aware information availability captures the lower importance of information that has been collected in the past while weighing more information that has been recently collected.

By combining Eq. 5 and Eq. 6, we define the geographical area's criticality c_m , as follows:

$$c_m = w_1 IA_{\mathcal{M}' \rightarrow m} + w_2 UI_{\mathcal{M}' \rightarrow m} \quad (7)$$

where $w_1, w_2 \in \mathbb{R}^+$, $w_1 + w_2 = 1$. The physical meaning of a geographical area's criticality c_m captures the preference that a user has to contribute information in an area with high demand for information collection.

Based on the above analysis, the user's payoff from contributing information in a geographical area depends on the monetary reward provided by the requester (first term of Eq. 8) and the intrinsic reward from contributing in the crowdmapping process (second term of Eq. 8), and is defined as follows:

$$P_j^{S_m} = \frac{I_j}{\sum_{\forall j \in S_m} I_j} \cdot r_m + c_m \quad (8)$$

Also, the user experiences a cost in order to collect and report the information in a geographical area and it is defined as follows:

$$c_j^{S_m} = c_t t_j + c_p p_j + c_v v_j \quad (9)$$

where $c_t, c_p, c_v \in \mathbb{R}^+$, $c_t < c_p < c_v$ express the unit costs per text length, and number of photos and videos provided to the requester, respectively. Thus, by combining Eq. 8 and Eq. 9, the user's overall utility by participating in a coalition S_m and providing its information in a geographical area m , is given as follows:

$$U_j^{S_m}(I_j, r_m, c_m) = P_j^{S_m} - c_j^{S_m} \quad (10)$$

III. HEDONIC COALITION FORMATION GAME FORMULATION

In this section, we formulate the problem of users' selection of a geographical area in order to support a crowdmapping task submitted by a requester, as a hedonic coalition formation game among the users.

Definition 1: (Users' Coalition) In a geographical area m , the users form a coalition $S_m \subseteq \mathcal{J}$ to support a crowdmapping task submitted by the requester.

Definition 2: (Grand Coalition) If $S_m = \mathcal{J}$, then all the users provide information in only one geographical area m .

Definition 3: (Empty Coalition) If $S_m = \emptyset$, then no user provides information in the geographical area m .

Definition 4: (Singleton Coalition) If $|S_m| = 1$, then only one user provides information in the geographical area m .

The users select to join a coalition S_m given the utility $U_j^{S_m}$ that they experience, aiming at maximizing their experienced utility. Thus, the users' preference operator over the available coalitions is defined as follows.

Definition 5: (Preference Operator) A preference operator $\geq_j$ for each user $j \in \mathcal{J}$ is defined as the complete and binary selection of a coalition S_m over all the available coalitions $S_{m'}, \forall m' \in \mathcal{M}$ as follows:

$$S_m \geq_j S_{m'} \Leftrightarrow U_j^{S_m} \geq U_j^{S_{m'}} \quad (11)$$

where $U_j^{S_m}$ is given by Eq. 10. In the case of strict selection of a coalition S_m , i.e., $>_j$, we have:

$$S_m >_j S_{m'} \Leftrightarrow U_j^{S_m} > U_j^{S_{m'}} \quad (12)$$

Definition 6: (Users' Partition) A set $\Pi = \{S_1, \dots, S_m, \dots, S_M\}$ is defined as the users' partition in the geographical areas M , with $S_m \cap S_{m'} = \emptyset, \forall m \neq m'$, and $\bigcup_{m=1}^M S_m = \mathcal{J}$.

The users participate in a hedonic coalition formation game aiming at autonomously choosing the coalition that will maximize their utility $U_j^{S_m}, \forall j \in \mathcal{J}, \forall m \in \mathcal{M}$, while considering the impact of the choices of the rest of the users.

Definition 7: (Hedonic Coalition Formation Game) The pair $(\mathcal{J}, >)$, where $\mathcal{J}$ is the users' set and $> = [>_1, \dots, >_j, \dots, >_J]$ is their preference operator vector, defines a hedonic coalition formation game.

The users prefer to contribute information to geographical areas, and corresponding crowdmapping tasks which have the potential to provide higher utility to them. Also, the overall crowdmapping process is dynamic and the users' coalition selection strategies impact the others, resulting in dynamically switching coalitions.

Definition 8: (Switch Coalitions) A user j , who has selected a coalition S_m , will switch coalitions from S_m to $S_{m'}, m \neq m'$, iff: $S_{m'} \cup \{j\} >_j S_m$. Then the coalitions will be updated, as follows: $S_m \rightarrow S_m \setminus \{j\}$ and $S_{m'} \rightarrow S_{m'} \cup \{j\}$.

A users' partition $\Pi = \{S_1, \dots, S_m, \dots, S_M\}$ is characterized as Nash-stable partition if no user has the incentive to unilaterally change coalition, given the coalitions selection of the rest of the users, as it will not achieve a higher utility.

Definition 9: (Nash-stable partition) If $S_m >_j S_{m'} \cup \{j\}, m \neq m', \forall j \in S_m, \forall S_m \in \Pi$, where $\Pi = \{S_1, \dots, S_m, \dots, S_M\}$, then, Π is a Nash-stable partition.

A users' partition can also be individually-stable if the users do not have the incentive to change coalitions, and if a user decides to join a new coalition, its decision will not reduce the utilities of the members of the new coalition.

Definition 10: (Individually-stable partition) Iff $\mathcal{S}_{m'} \cup \{j\} \succ_j \mathcal{S}_m, m \neq m', \forall m \in \mathcal{M}$ and $\mathcal{S}_{m'} \cup \{j\} \succ_{j'} \mathcal{S}_{m'}, \forall j' \in \mathcal{S}_{m'}$ do not hold true, then the users' partition $\Pi = \{\mathcal{S}_1, \dots, \mathcal{S}_m, \dots, \mathcal{S}_M\}$ is individually-stable.

In this paper, our goal is to show the existence of a Nash-stable and individually-stable users' partition in the geographical areas, where the requester announces crowdmapping tasks, and the users provide information. Furthermore, based on the requester's allocation of rewards per geographical area, it can strategically guide the users' partition to avoid participation holes in the different submitted crowdmapping tasks.

IV. STABLE COALITION FORMATION

In this section, we first show that the hedonic coalition formation game among the users in the crowdmapping process always has a Nash-stable and individually-stable users' partition $\Pi = \{\mathcal{S}_1, \dots, \mathcal{S}_m, \dots, \mathcal{S}_M\}$. Subsequently, we introduce a distributed algorithm that converges to the stable coalition formation.

Theorem 1: The hedonic coalition formation game among the users always has and converges to a Nash-stable and individually-stable partition $\Pi^* = \{\mathcal{S}_1^*, \dots, \mathcal{S}_m^*, \dots, \mathcal{S}_M^*\}$, starting from any random initial partition $\Pi = \{\mathcal{S}_1, \dots, \mathcal{S}_m, \dots, \mathcal{S}_M\}$

Proof: The proof is performed by contradiction. Initially, we assume that the users' final partition Π^* is not Nash-stable. This implies that some users prefer to switch coalitions and join other ones in order to ultimately experience a higher utility. Thus, the partition Π^* is not the final partition, which contradicts our initial assumption that the final partition Π^* is not Nash-stable. Therefore the hedonic coalition formation game always converges to a Nash-stable partition Π^* . Based on Definitions 9 and 10, it is evident that if a partition Π^* is a Nash-stable, then, it is also individually-stable. ■

Algorithm 1 below presents the GAIA (Hedonic Coalition Formation Algorithm), which is a distributed algorithm enabling the users to select to which crowdmapping task they will provide their information to, and the requester to appropriately allocate rewards to the users to incentivize them to participate in the crowdmapping process. The complexity of the GAIA algorithm is $O(SO)$, where SO is the number of switch operations performed by the users until they converge to the Nash-stable and individually-stable partition Π^* . Towards decreasing the computational complexity of the GAIA algorithm, we introduce the following preference utility function for the users:

$$PU_j^{\mathcal{S}_m} = \begin{cases} U_j^{\mathcal{S}_m}, & \text{if } \mathcal{S}_m \notin h(j) \\ -\infty, & \text{otherwise} \end{cases} \quad (13)$$

where $h(j)$ denotes the coalitions that user j has selected in the past.

V. NUMERICAL RESULTS

In this section, aiming at validating the operation of the proposed dynamic crowdmapping framework, we have performed a detailed simulation-based evaluation considering the

input data set of $J = 17$ real users aiming at contributing crowdsourcing data in $M = 5$ geographical areas. Specifically, in Section V-A, the pure operation and the performance of the proposed crowdmapping framework is discussed in detail, while in Section V-B, the impact of the reward and the geographical areas criticality on the crowdmapping process are analyzed and quantified. Section V-C introduces a scalability analysis of the proposed framework and Section V-D provides a comparative evaluation in order to demonstrate its efficiency and robustness. The users' amount of information is $\mathbf{I} = [5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37] \cdot 10^3$, the uncertainty of the information integrity follows a random distribution, and the overall model has been studied for 24 timeslots. Unless otherwise explicitly stated, the following parameters have been used throughout our evaluation: $w_t = 0.1, w_p = 0.3, w_v = 0.6, w_1 = 0.7, w_2 = 0.3, c_t = 0.1, c_p = 0.3, c_v = 0.6, \mathbf{r} = [10, 10.5, 11, 11.5, 12] \cdot 10^2, \mathbf{c} = [6.5, 7, 7.5, 8, 8.5] \cdot 10^2$.

Algorithm 1 GAIA: Hedonic Coalition Formation Algorithm

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1: Input:  $\mathcal{J}, \mathcal{M}$ 
2: Output:  $\Pi^* = \{\mathcal{S}_1^*, \dots, \mathcal{S}_m^*, \dots, \mathcal{S}_M^*\}$ 
3: Initialization:  $\Pi^* = \emptyset$ , create an initial partition  $\Pi$  by
   randomly allocating the users  $J$  to the geographical areas
    $M$ , initialize the history set of the coalitions for each user
   as  $h(j) = \mathcal{S}_m, \forall j \in \mathcal{J}$ .
4: Switch coalitions
5: while  $\Pi \neq \Pi^*$  do
6:   Update the final partition as  $\Pi = \Pi^*$ ;
7:   for  $j = 1$  to  $J$  do
8:     Determine  $PU_j^{\mathcal{S}_m}$ ;
9:     for each coalition  $\mathcal{S}_{m'} \in \Pi, m \neq m'$  do
10:      Determine  $PU_j^{\mathcal{S}_{m'}}$ ;
11:      Compare  $PU_j^{\mathcal{S}_m}$  and  $PU_j^{\mathcal{S}_{m'}}$ ;
12:      if  $PU_j^{\mathcal{S}_{m'}} > PU_j^{\mathcal{S}_m}$  and  $\mathcal{S}_{m'} \notin h(j)$  then
13:        user  $j$  switches from  $\mathcal{S}_m, \mathcal{S}_m \leftarrow \mathcal{S}_m \setminus \{j\}$  and
        joins  $\mathcal{S}_{m'}, \mathcal{S}_{m'} \leftarrow \mathcal{S}_{m'} \cup \{j\}$ ;
14:        Update the partition  $\Pi$  as  $\Pi \leftarrow \Pi \setminus \{\mathcal{S}_m, \mathcal{S}_{m'}\}$ 
         $\cup \{\mathcal{S}_m \setminus \{j\}, \mathcal{S}_{m'} \cup \{j\}\}$ ;
15:      end if
16:    end for
17:   end for
18: end while
19: return  $\Pi^*, \frac{I_j}{v(\mathcal{S}_m)} \cdot r_m, \forall m \in \mathcal{M}, \forall j \in \mathcal{J}$ 

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A. Pure Operation & Performance

Specifically, Figs. 1a - 1c present the switch operations of the users until they converge to the Nash-stable and individually-stable partition Π^* , as presented in Section IV, and quantifies their corresponding utility. It is noted that the users are initially randomly allocated to coalitions and by playing the hedonic coalition formation game, they ultimately converge to selecting the coalition that concludes to the maximum possible achieved utility, given the coalition selection strategies of the rest of the users.

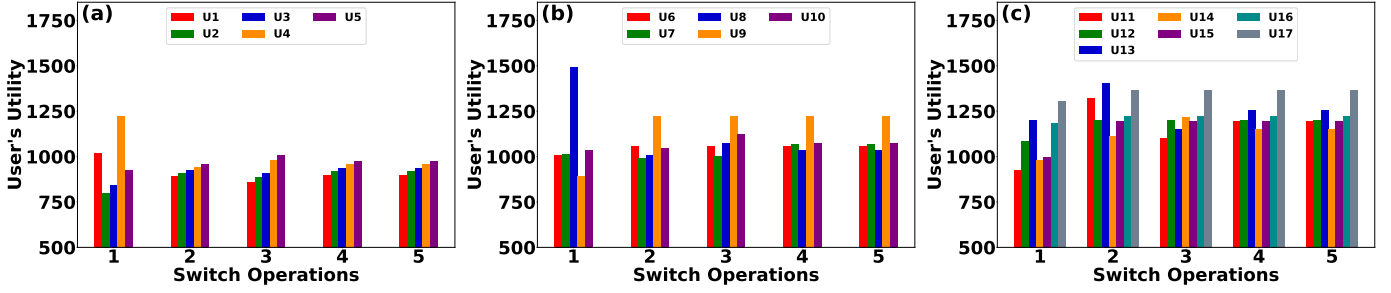


Fig. 1: Switching operation convergence to the optimal crowdmapping task selection.

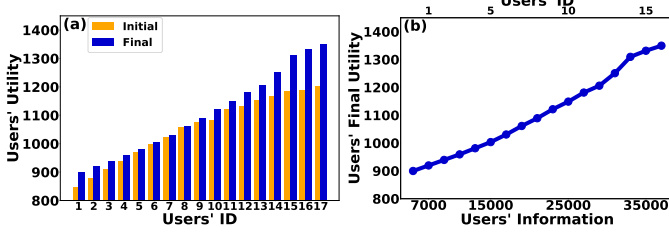


Fig. 2: Users' utility in the crowdmapping process.

Indeed, the results demonstrate that the vast majority of the users converge to a higher utility compared to the one experienced following the initial random allocation to coalitions. Also, it is highlighted that the GAIA hedonic coalition formation algorithm converges fast to the Nash-stable and individually-stable partition Π^* , as only 5 switching operations are needed for a set of $J = 17$ users, which corresponds to a few milliseconds.

Figs. 2a - 2b present the users' utility at the beginning of the hedonic coalition formation game (initial) and the corresponding achieved utility (final) after the GAIA hedonic coalition formation algorithm has converged to the Nash-stable and individually-stable partition Π^* as a function of the user's ID (where the users are sorted with respect to the amount of information that they contribute to the requester), and the users' final achieved utility as a function of the amount of contributed information, as defined in Eq. 1. The overall framework has been executed for 10,000 instances following a Monte Carlo analysis. The results reveal that the users achieve a higher utility at the end of the hedonic coalition formation game, given that they have intelligently selected to contribute their information in a geographical area that they ultimately receive a higher reward from the requester, as well as the selected area is characterized by high criticality in terms of needing a large amount of information (Fig. 2a). Also, it is demonstrated that the proposed hedonic coalition formation algorithm is fair, as the users who contribute a larger amount of information, ultimately achieve a higher utility (Fig. 2b).

B. Impact of Reward & Criticality

In this section, the impact of the requester's allocated reward r_m per crowdmapping task, i.e., geographical area, and of the criticality c_m of the geographical area, on the partition of the users into the corresponding coalitions is studied.

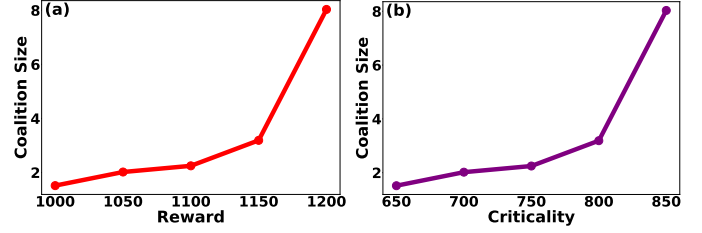


Fig. 3: Impact of reward and geographical areas criticality on the crowdmapping task selection process.

Specifically, Figs. 3a - 3b present the coalition size of the five examined geographical areas as a function of the reward and the criticality, respectively. A Monte Carlo analysis of 10,000 instances has been performed.

The results show that the requester can strategically guide the decisions of the users in terms of contributing their information in a geographical area by appropriately allocating a higher overall reward to an area that is characterized by a higher need in terms of collecting information. Specifically, based on Fig. 3a, we observe that the users select to contribute their information to the areas that are characterized by a higher overall reward, thus, the coalition size increases as the requester's allocated reward increases. Similarly, a geographical area that is characterized by a higher criticality drives the users' preference to contribute their information to this area. Thus, the coalition size increases as the criticality of the geographical area (and respectively of the corresponding crowdmapping task), increases (Fig. 3b).

C. Scalability Analysis

In this section, a scalability analysis of the proposed GAIA hedonic coalition formation algorithm is provided in order to show its efficiency and robustness. Specifically, a large-scale system is considered with up to 200 users contributing information in five geographical areas. Fig. 4 presents the users' switch operations (left vertical axis) and the corresponding execution time (right vertical axis) of the proposed GAIA hedonic coalition formation algorithm as a function of the number of users participating in the crowdmapping process. The results reveal that the number of switch operations and the corresponding execution time increase with respect to the number of users participating in the crowdmapping process. However, given the low computational complexity of the pro-

posed algorithm, the overall execution time remains relatively low in terms of a real-life implementation of the proposed model. Specifically, the results show that for 200 users participating in the crowdmapping process, less than 0.4 sec is required in order for the users to perform their autonomous decision-making in terms of selecting the crowdmapping task.

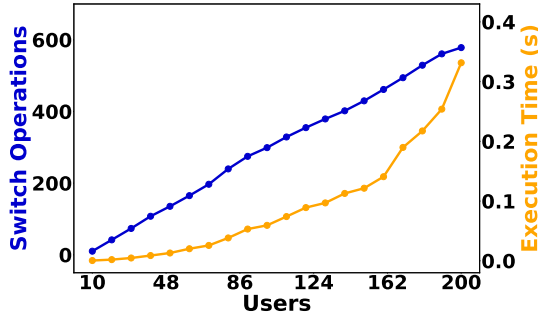


Fig. 4: Scalability analysis.

D. Comparative Evaluation

In this section, a comparative evaluation of the proposed GAIA crowdmapping model is performed in order to demonstrate the benefits of the hedonic coalition formation game-theoretic approach in terms of users' achieved utility and scalability of the overall crowdmapping solution. Specifically, the GAIA crowdmapping model is compared against the following alternatives: (i) Random, (ii) Reward, and (iii) Criticality, where the users select either randomly a crowdmapping task (i.e., geographical area) or based on the largest reward, or based on the criticality, respectively. It is noted that the criticality value of each geographical area is kept the same under the Reward scenario, and similarly, the reward value of each area is the same for the Criticality scenario, in order to capture the impact of each degree of freedom per scenario.

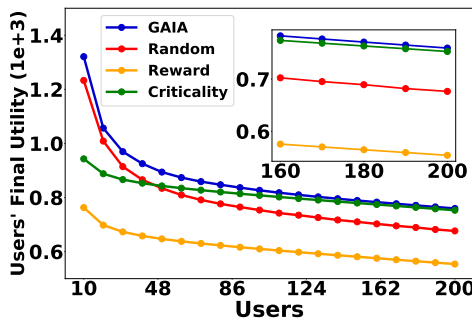


Fig. 5: Comparative analysis.

Fig. 5 presents the users' final achieved utility after the users select a stable coalition as a function of the number of users contributing to the crowdmapping process. The results reveal that the Reward scenario presents the worse benefit for the users, as all of them gather in one coalition sharing the fixed allocated reward to that area. On the other hand, the Criticality scenario presents better results compared to the Reward scenario, as the criticality of a geographical area is not a shared-type of resource among the users (as is the reward) and provides the same benefit to every user, even if all users contribute their information to one crowdmapping task. The

GAIA crowdmapping model achieves the best utility for the users among all the comparative scenarios, as it jointly exploits the reward and the criticality of a crowdmapping task in order to coordinate the users' information contribution.

VI. CONCLUSION

In this paper, the crowdmapping problem is studied considering that a requester announces different crowdmapping tasks in different geographical areas and provides the appropriate rewards to the users in order to incentivize them to participate in the crowdmapping process. A hedonic coalition formation game is introduced among the users in order to enable them to autonomously select the geographical area and the corresponding crowdmapping task where they will contribute their available information. Based on the proposed hedonic coalition formation game, the requester allocates the rewards to the users considering their quality and quantity of information. The existence of a Nash-stable and individually-stable partition of the users to the announced crowdmapping tasks is proven and a distributed hedonic coalition formation algorithm is introduced that converges to the corresponding solution. A detailed set of numerical results are presented that demonstrate the pure operation, performance and tradeoffs of the proposed crowdmapping model. Part of our current and future work is the extension of the proposed model by considering multidimensional rewards that can be provided by the requester to the users and their impact on the users' decision-making process, such monetary rewards, points-based rewards (i.e., leaderboards), and intrinsic rewards [10].

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