This is a post-print version of the paper. The final version is available at https://doi.org/10.1016/j.future.2020.02.035

# A Meritocratic Trust-based Group Formation in an IoT Environment for Smart Cities

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**Abstract**

Smart cities are built on top of heterogeneous IoT infrastructures, that can be viewed as communities of software agents (the intelligent objects) that interact with each other to realize complex activities. These agents operate on behalf of users that need services; for these reason agents are often in competition with each other. On the other hand, an agent can often benefit from collaborating with other agents in some circumstances, exchanging information and services. Under this viewpoint, the task of finding the best partners to collaborate is a key task for an agent. A general consensus exists about the benefits deriving by forming friendships and groups for mutual cooperation inside competitive Multi-Agent Systems (MASs). In this respect, the existing proposals are usually addressed to maximize the profit at the level of individual agent or group. Unfortunately, the most part of these approaches could advantage the most aggressive agents, also in presence of bad social behaviors. This is not a desired scenario in a smart city environment. A possible solution to this problem is that of promoting correct behaviors and meritocracy inside agent communities. To this aim, we propose to model the competitive MAS scenario in the framework of non cooperative games by assuming to represent *i*) the trustworthiness of agents relationships by means of a trust model and *ii*) the capability of a community to provide its members with a good environment by means of its social capital. As a result, a group formation algorithm capable to asymptotically maximize the social capital is proposed. This algorithm highlights two main features: *i*) the computed solution is a Nash equilibrium in the considered game and *ii*) the only rewarded agents are those having the most correct behaviors.

*Keywords:*
Smart City; Internet-of-Things;Competitive Agents; Group; Meritocracy; Nash equilibrium; Trust

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## 1. Introduction

The development of the Smart City paradigm implies to exploit different advanced information technologies, as networking communication infrastructures, sensor networks and Internet-of-Things (IoT), to realize multidimensional aggregation of information [1, 2]. In a smart city environment, we can imagine that a large set of smart software agents, associated with intelligent objects of an IoT infrastructure, communicate and inter-operate to integrate collected information deriving from sensors, in such a way that the whole system can provide analyses that meet the demand of the people for obtaining intelligent services and decision support. This scenario emphasizes how the smart city can support public services as the city management, government, industry, thus improving the efficiency of the services and the people's quality of life.

In this perspective, a smart city based on an IoT infrastructure can be viewed as a community of software agents (the intelligent objects) that interact with each other to realize more or less complex goals. These agents operate on behalf of users that require them a service (e.g. obtaining a certification from a public office, finding a new job, determining the most suitable path for reaching a destination with the public transportation, etc.) and to reach their goals are often in competition with each other. As an example, the agent that operates for finding a job for its user, is in competition with other agents that perform a similar task for their own users. On the other hand, an agent can often benefit from collaborating with other agents in some circumstances, exchanging information and services.

Examples of these applications are city tour planners [3] or activities recommendation systems [4]. In this perspective, an automatic outdoor planning system of a city tour must consider that groups of users jointly select the activities to perform, and therefore it is necessary to choose activities maximizing the group satisfaction, taking into account that members preferences can be different.

Under this viewpoint, the task of finding the best partners to collaborate is a key task for an agent. When an agent community is formed by self-interested agents, which do not act in the interest of a global outcome but only in their own [5, 6, 7], the community has a competitive nature and it also implies that the agent cooperation taking place therein cannot be a priori assumed as sincere. In other words, it means that the potential partners of an agent are also its competitors and some of them could deceive in carrying out an interaction with it. Therefore, it is evident as both incomes and outcomes of an agent tightly depend on the choice of its partners.

An important role in the development of virtual societies formed by software agents representing the intelligent objects of an IoT infrastructure (i.e., software entities supporting human and virtual users with useful services) is played by group formation processes where group members can receive significant benefits from their mutual collaborations.

For instance, e-services, like e-Learning or e-Government, typical in a smart city, have considerably taken advantage from this agents role. An example can be found in [8], where artificial intelligence techniques such as Bayesian learning, coalition structure formation, and Belbins role theory are combined together to support the creation of working groups in an educational context. In particular, this approach considers the problem of finding optimal teams as a problem of coalition structure generation, which is solved by adopting a linear programming method to optimize a social welfare function. However, in this case, the agents are not competitive so that the only goal of this framework is to optimize the social welfare.

Differently, in presence of competitive agents, the task of forming effective groups should satisfy the perspectives of both *i*) the social community, interested to optimize a global social welfare, and *ii*) the single agent, interested in maximizing its own payoff.

This scenario has been well formalized in the context of trust-based agent communities and the different aspects related to the concept of trust within a community have been widely investigated in the literature, where a clear connection is reported between *trust* and *social capital* [9, 10, 11].

Social capital refers to a global value associated with a group of individuals and it is considered as the most relevant asset existing in a social community. More specifically, it has been defined as "the density of interactions that is beneficial to the members of a community" [12] that allows us to link trust measures with the benefits that a user can receive from his/her affiliation to a social network or, similarly, the advantages that a social network can receive from accepting a new membership.

We clarify the important aspect of the dynamic nature of trust measures, since the trust perceived by an agent $a$ with respect to another agent $b$ is the result of the several interactions between the two agents, and thus varies in time, but it also depends from new information that continuously can be obtained from $a$ interrogating the other agents of the community, and this leads to a further possible changes of the trust values.

To improve the agent cooperation within a community, an effective solution is that of realizing therein a social organization among the agents associated with intelligent objects. In particular, if an agent has a set of *friends* (i.e., denoted as its *friendship set*) and it can join with one or more *groups*, then it can benefits to receive a collaboration from one or more friends and/or groups (of which it is member) for free.

Therefore, by defining the social capital as the global advantage, in terms of trust, that the whole community receives from its organization, we can assume, from a social viewpoint, that the better the internal organization of a community, the higher the maximization of its social capital. Nevertheless, we highlight that this solution does not necessarily maximize the payoff of each agent.

A great attention has been given to the problem of coalition formation in a multi-agent system scenarios [13, 14]. This problem can be formulated as "How can we form agent teams in a smart city context, where a specific task is assigned to each team, in order to best complete the set of tasks at hand?" The best solution would be finding the coalitions allowing to maximize the sum of coalition values, by assuming it as the social capital of the community.

To this aim, a great number of approaches maximizing the utility (i.e., some type of *profit* measure) of a single agent or a group have been proposed [14]. Anyway, this sort of approach could have some negative side-effects. Indeed, from one hand, if the maximization of the local profit is the goal, it could lead to reward the most *aggressive* agents also in presence of bad social behaviors (e.g., misleading activities); while, from the other hand, if the maximization of the global profit is the goal, then the most deserving agents could have not recognized their merits for a kind of *social flattening* due to the adopted approach.

In a MASs context the presence of competitive agents has been contemplated also by taking into account the role of trust [15, 16], even though the possibility for self-interested agent to form groups for allowing them to collaborate has not been considered. Recently, an increasing attention has been given to study the problem of forming effective social structures (e.g., friendships and groups) in competitive environments, as social networks and grid/cloud agent communities, but exclusively under a social capital viewpoint without involving the relationship existing between social advantage and the individual interest of the single agent [10, 17].

Game theory [18] provides an important indication on the formation of effective groups. In particular, the solution proposed in this paper belong to the Nash equilibrium [19], which can be described as kind of stationary states where any player can take benefit by the application of a strategy changes while the other players keep theirs unchanged. Indeed, differently from maximizing an individual or a global profit, we propose a solution based on forming friendships and groups that tries to optimize the social capital ($SC$) that we represent by means of the mutual trust relationships. In order to reach this result, we developed the *Friendship and Group Formation* (FGF) algorithm, by adapting the Users-to-Groups (U2G) algorithm presented in [20], for using as optimization function the form of social capital above introduced.

As main contribution, we will show that the FGF algorithm holds two important features, particularly important in the specific context of a smart city:

- A kind of meritocracy is introduced into the framework by rewarding effective agent performances and, at the same time, by promoting their correct behaviors. This appears specifically desired in a social environment as a smart city. To this aim, two main theoretically contributions are provided:
    1. a theoretically prove that the FGF algorithm enhances the social capital of the community.
    2. a prove that the FGF algorithm, along the competition process, rewards those agents exhibiting the most *virtuous* behaviors; in other words, those agents perceived by the community as the most competent and honest.
- We will prove that the solution provided by the FGF algorithm corresponds to a Nash equilibrium [19]. To this aim, a friendships and groups formation has been modeled as a strategic non cooperative game. In a smart city context, this assures that the solution is the most reasonable as possible, mediating from the different users' goals.

As we will discuss in the remaining of this paper, the two features above discussed make our solution optimal *i*) from a social viewpoint and also *ii*) as one of the most rational from the individual viewpoint of each agent.

We highlight that, from the viewpoint of a practical application in a smart city context, our approach introduces the actual possibility of constructing groups of IoT objects that collaborates for improving the effectiveness of the whole system, represented by the social capital of the IoT community, guaranteeing on the other hand that the individual advantage of each member is not penalized, but it is the maximum obtainable in such an intelligent community, provided with a meritocratic mechanism. We also notice that the distributed nature of the FGF algorithm, that is a variant of the well-known U2G algorithm, is particularly suitable to be applicable in large scale situations (see [20]). As a final observation, we want to highlight that our proposal, although particularly suited to be applied in a smart city context, is not bound to that environment and can be useful in other large scale Internet-based platforms.

The rest of the paper is organized as follows. In Section 2 some related work are discussed. In Section 3 the reference scenario for IoT competitive agents is described, while Section 4 presents the trust model. Section 5 introduces the FGF algorithm we designed to form friendships and groups, while Section 6 contains a few relevant theoretical results. Section 7 provides a qualitative analysis of our approach through two interesting scenarios of applications, while Section 8 provide a quantitative analysis by means of a number of simulations. Finally, in Section 9 we draw our conclusions and present our ongoing research.

## 2. Related Work

This section presents a number of works related to partner selection and collaboration among self-interested agents. In particular, partner selection has a significant role in filling the deficit of distributed agents. To this aim, the related research proposes various kind of evaluation metrics aimed at selecting the most appropriate partners. These mechanisms can be classified into three categories: local decision with local modeling, negotiation-based approach, and middle agents.

### *2.1. Group formation in Smart Cities / Iot environments*

Several works in the past literature deal with a smart city scenario in which software agents are interested in forming groups to effectively performing their tasks. As an example, [21] faces the problem of providing users with recommendation and decision support systems for smart city applications relying on the analysis of the users' behaviors on social communities. Examples of these applications are city tour planners or activities recommendation systems. In this perspective, an automatic outdoor planning system of a city tour must consider that groups of users jointly select the activities to perform, and therefore it is necessary to choose activities maximizing the group satisfaction, taking into account that the members preferences can be different. As another example, [22] considers that many smart city applications involve groups of individuals that wish to remain together as they move throughout the city. For example, a group of tourists may be monitored by a tour operator to keep the group together and on schedule, or a group of school children should be closely supervised by an adult to ensure the children stay safe. In this context, the paper introduces LASSO, a smartphone-based service that exploits wireless devices carried by each group member to provide infrastructure-free group formation and monitoring. In [23], the authors consider that Mobile crowdsensing (MCS) leverages participation of active citizens to improve performance of existing sensing infrastructures. In typical MCS systems, sensing tasks are allocated and reported on individual-basis, and the paper investigates on collaboration among users for data delivery as it brings a number of benefits for both users and sensing campaign organizers and leads to better coordination and use of resources. Moreover, in [24] the authors highlight that the problem of guaranteeing ubiquitous network connectivity is challenging, due to the heterogeneous and resource-constrained characters of Internet of Things (IoT). In this setting, they stimulate effective cooperation among user equipment and propose a social-aware group formation framework to allocate resource blocks effectively following an in-band NB-IoT solution. Finally, in [25], the authors argue that IoT and smart cities promote a vision of computational ecosystems in which autonomous agents with different capabilities are expected to cooperate towards global goals in dependable ways. In this context, they present a model for resilient, collaborative edge-enabled IoT that leverages spatial locality, opportunistic agents, and coordinator nodes at the edge.

### 2.2. Local Decision by Modeling Agents

Belief has been defined as a situational awareness. Previous investigations about belief revision in multi-agent systems pursues a similar objective: build the agents' beliefs accurately and efficiently by using all the information provided [26, 27, 28]. In these approaches, the beliefs are assigned preferences by epistemic relevance in a symbolic logic [29], or ordered by credibility in [30] using belief function. Also, preferences can be determined by evaluating the information source trustworthiness by using Bayesian networks [27] soft or a statistical approach [28]. Exact inference adopting these approaches is computationally expensive [31, 32, 33], so there have been approximate inference approaches which reduce the complexity of computation [34, 35, 36]. However, those approximate inferences are applicable to the specific belief revision algorithm targeted by the respective scheme.

In the information exchange domain, research on belief revision for local decision also involves how to select appropriate information providers. Local decision and local modeling [33] consider the local model about potential partners and finds the most appropriate of them [37], for instance, on the basis of trustworthiness, reputation or quality of provided services. These models are built either by direct observation or by communication occurring with other agents. In social control research, agents need to evaluate other agents or the services they provided for realizing a distributed and secure control over the interactions occurring among agents [38].

The methods for selecting appropriate service providers based on quality of service (QoS) among Web services is proposed in [39, 17]. Maximilien et al. [39] distinguish interactions of service providers and consumers into three phases: discovery, selection, and binding. For the selection phase, they associate nonfunctional attributes such as capacity of a service, and response time to represent the quality of services (i.e., a reputation shared by all agents). With this evaluation of service quality, the selection problem can be simplified to picking up the most trustworthy services. While this approach provides a practical solution to selecting the most trustworthy partners based on the quality of Web services, it lacks the ability of handling dynamic changes in service consumers' requirements. In other words, this approach can work well for a one-shot interaction or iterated interactions for a single service. However, it does not consider the case where the current or future service requirements are dependent on the previous interactions.

### 2.3. Negotiation-based Partner Selection

In the negotiation-based approach are involved explicit peer-to-peer communication carried out for negotiation. For instance, in [40, 41, 42] is presented the Contract Net Protocol (CNP) which provides a mechanism to find the best partners by providing services at the lower cost. Research on coalition formation among self-interested agents often adopts the negotiation mechanism so that agents can figure out who the best candidates are for forming a coalition. CNP is a fully automated negotiation protocol where each agent can be an initiator or a participant. After an initiator sends out a call for proposals, participants bid on that call and the initiator selects the best bids while rejecting other bids. Negotiation is useful especially when there are no arbiters. Although CNP provides a relatively simple mechanism for partner selection, it can still be computationally expensive in large-scale systems because of the message complexity. Also, CNP may be vulnerable to the situation where commitment to the contract is not guaranteed. In other words, agents need to be cooperative for CNP to work. This protocol has been adopted in Transportation Cooperation Net (TRACONET) [43] for a vehicle routing application, and has also been standardized in Foundation for Intelligent Physical Agents (FIPA)[1] as an interaction protocol among agents.

In [44], the Adaptive Decision Making Framework (ADMF) also adopts a negotiation-based partner selection scheme. ADMF is designed for a system where agents have shared global goals and the structures among agents are targeted to maximize these global goals. In particular, agents are able to dynamically reorganize the structure of a group of agents to meet the needs of their current situation. ADMF provides a spectrum of power relations between agents, from locally autonomous to master-slave. ADMF allows a dynamic adjustment of agents' relationships but because of the complexity of the negotiation process ADMF can suffer a scalability problem in a large-scale system. Also, due to the assumption about commitment to the agreement, the agents are assumed to be cooperative.

Coalition formation seeks to partition the agents in a system into groups which maximize the utility of the group or the individual agent. The partitioning of the agents is usually modeled as a characteristic function game and involves three activities [43]: coalition structure generation, solving the optimization problem of each coalition, and pay-off division. The first two activities are closely related to finding appropriate partnerships from a set of potential groupings, while pay-off division is to decide how the utility gained by forming a coalition should be distributed among the agents to keep the coalition stable. Pay-off division has been a major issue in the coalition formation research and it is useful for maintaining or encouraging agents' collaboration, but recent focus has been on coalition structure generation [45, 46, 47, 48] in addition to the earlier research [49, 50, 51, 52].

Generally, the formation of a coalition involves the negotiation process. In [50], Ketchpel has identified four phases of coalition formation: the communication phase, calculation phase, offers phase, and unification phase. The communication phase locates other agents that may have compatible or overlapping goals, or agents that may have complementary skills. When an agent communicates with potential partners, the information which is necessary to calculate the Shapley value (i.e., this value represents each agent's aggregated contribution to the coalition, and it is dependent on the order of agents joining the coalition [53]) is delivered to the potential partners. In the calculation phase, the Shapley values for each permutation of the coalition structures are calculated. It is an exponential operation, so the calculation is limited to pairs of agents only. Each agent creates a preference ordering of the partners based on the calculated Shapley value. In the offers phase, the matching is decided by using a modified stable marriage algorithm [53]. When a pair of agents forms a stable matching, they form a coalition in the unification phase, and in the next round of communication, the coalition acts as a single agent. This process of inter-

[1] www.fipa.org, 2018

action and negotiation to form a coalition makes the membership global to the agents, meaning the agents, at least in the same coalition group, know who is in the group. On the other hand, partner selection in this research gives a local perspective of partnerships, meaning that only the information consumers know who is partnering with them.

Most of the coalitions are disjoint [49, 47, 50, 54] except [52]. Shehory et al. [52] provide an approach to allow overlapping coalitions, meaning an agent can be a member of more than one coalition. Agents can provide the same information to multiple consumers, and can also handle multiple instances of information. The overlapping membership is possible via the precedence ordering of goals, and it reduces the waste of resources and capabilities. Although Klusch et al. [48] investigate the coalition formation in an open and dynamic environment, the resulting coalition is stationary. Banerjee et al. [47] also proposed a stationary coalition formation based on structure and probability of the pay-off. The authors assume that there are a finite number of interactions, and find the static partnership during the given number of interactions. These stationary coalition structures do not work in an open environment. The coalition formation process is also computationally expensive. For example, the stable marriage algorithm [50] or set covering algorithm [54] used to find the best coalition structure requires a significant amount of computational resources. Some research focuses on the efficiency of the coalition structure generation [46, 49]. Sandholm et al. [49] focused on the resource-bounded agents and proposed an anytime algorithm, which has the worst case bound. Dang et al. [46] improve the efficiency of Sandholm's algorithm while keeping the worst case bound guarantee. Some of the approaches assume super-additivity [50, 54], which may not hold in the real-world problem. There are costs for forming a coalition, and these costs should be taken care of. The proposed approach in this research takes care of the cost incurred by interacting with information sources by considering the tradeoffs between the benefits gained by the partnership and the costs of interactions.

### *2.4. Middle Agents*

Using middle agents [55] represent another kind of partner selection mechanism. A middle agent is an arbiter who actually helps agents find partners based on preferences or capabilities. Middle agents have been used in various application areas such as service discovery, lookup solutions for peer-to-peer networks, information retrieval, referral network, and Web-services [56, 57, 58, 59, 60]. While middle agents provide a practical solution for partner selection, the agents who want to contact the middle agents need to follow the communication protocol, which may not be always available for every agent. Also, a single failure point from a single middle agent can cause a problem although it is possible to use various fault-tolerant schemes. Scalability is another issue, but hierarchical middle agents can improve the scalability to some degree.

Recently, the use of trust in competitive agent systems has been widely emphasized [61]. In this context, trust measures have been exploited for forming clusters of agents [62, 63] and for generating recommendations in social network contexts [64].

None of the aforementioned approaches faces the issue of improving the social capital of the agent community by introducing meritocracy. Instead, those approaches try to use trust measures for recommending to an agent the best agents to contact as promising interlocutors, without the purpose of introducing a social advantage for the whole community. Instead, our approach is capable of achieving such an advantage, also realizing it through a meritocratic approach, that encourages the social actors to assume correct behaviors for increasing their social reputation.

## 3. The reference scenario

Let $U$, $A$ and $C$ be the sets, respectively, of *i*) users, *ii*) IoT agents that compete to satisfy users' demands and *iii*) predefined categories. When a user $u \in U$ makes a request $r_\rho$ for the service $s$ belonging to the category $\rho \in C$ to an agent $a \in A$, then $u$ accepts to pay a price $p$ to the agent $a$ providing $s$.

Each agent $a$ has an expertise $E_a(\rho)$ for each category $\rho \in C$ representing its capability of providing good services falling in $\rho$. $E_a(\rho)$ is a real value belonging to the domain $[0..1]$, where 1/0 means that the agent $a$ provides services having the maximum/minimum quality. At the end of the procedure, the user $u$ releases a feedback $f$ to $a$, where $f$ is a real value belonging to the domain $[0..1]$, such that 1/0 represents the maximum/minimum satisfaction that the user $u$ perceived.

Moreover, we assume that each agent $a$ has a set $F_a$ of *friend agents*, with $F_a \subseteq A$. Besides, our scenario provides the existence of some agent groups and let $G$ be the set of these groups, where each group $g \in G \subseteq A$ is a set of agents. As it is usual in multi-agent systems, the mapping $agents(g)$ is associated with a Directory Facilitator ($DF$) that receiving as input a group $g \in G$ then it returns the set of the agents that are members of $g$.

To satisfy a service request referred to the category $\rho$, the agent $a$ can send a *contribution* request to another agent $b$, that can accept or refuse it. In our scenario, we suppose that an agent can request a maximum number of $cMax$ contributions. More in detail, if the request of $a$ is accepted by $b$ and $b \in F_a \bigvee \exists g \in G : a, b \in g$ then the contribution request will be provided by $b$ to $a$ for free; otherwise $a$ has to paid a price $p_c$ to $b$ after $b$ has provided its contribution.

Moreover, the agent $a$ can require the opinion of the other agents in order to identify the best agents to require a contribution. In other words, $a$ sends to an agent $c$ a request to receive a recommendation $rec_b(\rho)$ about the expertise $E_b(\rho)$ of the agent $b$ in the category $\rho$. Also in this case, we suppose that an agent can request a maximum number of $rMax$ recommendations.

The agent $c$ can accept or refuse the request of $a$; if $c$ accepts this request then $a$ has to pay a price $p_r$ to it, but if $c \in F_a \bigvee \exists g \in G : a, c \in g$ then the recommendation will be provided by $c$ to $a$ for free.

## 4. Trust measures: service reliability, suggest reliability and reputation

In this scenario, we assume that some IoT agents are unable to provide services or correct suggestions. Indeed, an agent $b$ that received a request for a contribution from an agent $a$ could provide a service denoted by a low quality. Similarly, an agent $c$ that received a request for a recommendation from an agent $a$ about the agent $b$ could indicate a wrong value for the expertise of $b$.

To manage these cases, the agent $a$ associates with each agent $b$, with which $a$ interacted in the past, three trust values. The first value, denoted by S-REL(b,$\rho$)) is named *service reliability* of $b$ with respect to the category $\rho$; this value represents the level of trust that an agent has about the possibilities to receive good contributions from $b$ in services belonging to the category $\rho$.

When an agent $b$ provides a contribution for a service, then the agent $a$ will receive a feedback $f$ from a user. Formally, $f_b$ is mapping $h$ such that $f_b = h(f, info_b)$, where $f$ is the feedback and $info_b$ is a possible supplementary information that $a$ could receive about the actual contribution provided by $b$.

For example, suppose that the service provided by $a$ is represented by an integer value denoted by $x$. When the user $u$, in response to his/her request, receives $x$ then he/she provides the feedback $f$ as the percentage error with respect to the correct answer $r$. If we do not have any additional information $info_b$, then $f_b$ is assumed to be the percentage error associated with the contribution provided by $b$ with respect to the correct answer $r$ (i.e., $f_b = f$). In other words, in this case the agent $a$ simply transfers the responsibility of the feedback to its contributors. At the end, the service reliability S-REL(b,$\rho$) is computed as the arithmetical mean of all the feedback components associated with $b$, with respect to the feedback that $a$ received from users for services belonging to the category $\rho$.

The second trust value A-REL(b), is called *suggest reliability* of $b$ in providing a recommendation. A-REL(b) is computed by taking into account, for all the $l$ feedback components $f_c^1$,..,$f_c^i$,..,$f_c^l$ that $a$ received from users with respect to services provided by a contributor $c$ recommended by $b$, the percentage difference between $f_c^i$ and the recommendation $r_c^i$ provided by $b$ and associated with $c$ (i.e., $diff_i = \frac{|r_c^i - f_c^i|}{r_c^i}$). Therefore, A-REL(b) is the arithmetical mean of all the $diff_l$ values.

Finally, the last value $REP(b, \rho)$, associated with the category $\rho$, is named *reputation* of $b$. It represents how much the capability of $b$ in the category $\rho$ is perceived by the agents consulted by $a$. $REP(b, \rho)$ is computed as the weighted mean of all the recommendations, refereed to the category $\rho$, provided to $a$ about $b$ by the other agents, by assuming the weight of each recommendation provided by an agent $c$ as equal to A-REL(b).

If $b$ had no interaction with $a$, our model has an initial configuration. Or rather, for all the agents $b$ that $a$ did not contact in the past for contribution requests falling in the category $\rho$, S-REL(b,$\rho$) is set to $c_{S-REL}$. Similarly, for all the agents $b$ that $a$ did not contact for recommendation requests in the past, A-REL(b) is set equal to $c_{A-REL}$. Finally, for all the agents $b$ that $a$ did not contact in the past for which $a$ did not received recommendations falling in the category $\rho$, $REP(b, \rho)$ is set to $c_{S-REL}$. As cold start values for the agent $a$, the values $c_{S-REL}$, $c_{A-REL}$ and $c_{REP}$ are assumed.

As a synthetic trust measure, $a$ assumes the measure $trust(b, \rho)$=$\alpha\cdot$ S-REL$(b, \rho) + (1 - \alpha) \cdot REP(b, \rho)$ where $\alpha$ is a weight belonging to the domain $[0..1] \in \mathtt{R}$ giving the relevance that $a$ assigns to the reliability with respect to the reputation.

## 5. The *Friendship and Group Formation* (FGF) algorithm

As described in Section 1, contributions or a recommendations are provided for free only when they are required by an IoT agent to a friend or to a member of one of the groups which the agent belongs to.

Recall that an agent $a$ is directly connected with its friend $fr$ thanks their mutual decision, assumed in the past, to become friends. Differently, the agent $a$ and a group member $m$ could not be friend, but if $m$ is available to give contributions and recommendations to $a$ it will happen for free due to the fact they are affiliated to the same group.

For each category $\rho$ and at each instant, the agent $a$ maintains a set of *$\rho$-best contributors*, denoted as $BC_a^\rho$, formed by the agents with which $a$ interacted in the past for receiving a contribution falling in the category $\rho$. These agents must have the following characteristics: the highest $cMax$ trust values $trust(b, \rho)$ (i.e., $b \in BC_a^\rho$) and a trust value $trust(b, \rho)$ greater than a fixed threshold $t_S$. $BC_a^\rho$ contains the agents that $a$ would desire to contact for a contribution.

Similarly, a set of *best recommenders* $BR_a$ is computed by any agent $a$ to record those agents with which $a$ interacted in the past to obtain a recommendation, and that have both the highest $rMax$ capability in providing suggestions A-REL(b) (i.e., $b \in BR_a$) and the A-REL(b) value greater than a fixed threshold $t_A$. In other words, $BR_a$ is formed by the agents that $a$ would prefer to contact for having a recommendations.

Obviously, to obtain the maximum performances, $a$ would want to achieve the following goal:

$$\bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a = F_a \bigcup_{g \in G_a} g \tag{1}$$

This means that $a$ stores in $BC_a^\rho$ (for all the categories) and $BR_a$ only those agents that are in its set of friends $F_a$, or in some group $g \in G_a$ where it is affiliated with.

However, two disadvantageous situations can occur for the agent $a$: *i*) some agents that do not belong to $\bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a$ there exist in $F_a \bigcup_{g \in G_a} g$ and *ii*) some agents belonging to $\bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a$ are not belong to $F_a \bigcup_{g \in G_a} g$.

In this case, $a$ has to be available to satisfy for free a possible request of the agents belonging to $F_a \bigcup_{g \in G_a} g$ without to balance this cost with the opportunity of having, in its turn, the best agents from which obtaining contributions and/or recommendations.

In the condition *i*) the percentage of the agents $b \in F_a \bigcup_{g \in G_a} g - (\bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a)$ can represent the disadvantage for $a$ (with respect to the number of agents present in $F_a \bigcup_{g \in G_a} g$) because each one of these agents will not never contacted for help while, on the contrary, they could contact $a$ to have help for free.

In the condition *ii*), for each agent $b \in \bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a$ not belonging to $F_a \bigcup_{g \in G_a} g$, the disadvantage for $a$ is represented by the difference between $trust(b, \rho^*)$ and $trust(b^\circ, \rho^*)$, where $\rho^*$ identifies the category in which $b$ is one of the preferred agents and $b^\circ$ is the best alternative to $b$ that $a$ has in its set of friend agents (i.e., the agent of $F_a \bigcup_{g \in G_a} g$ having the best trust value in category $\rho^*$). If $b$ is the preferred agents in more categories, $\rho^*$ is the category associated with the highest trust value. The whole disadvantage may be assumed equal to the average of all these contributions.

This means that at each time the disadvantage of $a$ is given by the following formula:

$$D_a = \frac{\|F_a \bigcup_{g \in G_a} g - \bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a\|}{\|F_a \bigcup_{g \in G_a} g\|} + \frac{\sum_{b \in \bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a - F_a \bigcup_{g \in G_a} g} trust(b, \rho^*) - trust(b^\circ, \rho^*)}{\| \bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a - F_a \bigcup_{g \in G_a \|} g} \tag{2}$$

Clearly, if the equality 1 holds then $D_a = 0$, i.e. the disadvantage is minimum. In reverse, $D_a = 1$ (maximum value) if all the agents present in $F_a \bigcup_{g \in G_a} g$ are not the favorite contributors or recommenders and, contextually, all the alternative agents give a trust difference equal to 1.

In each epoch some preferred agents are joined to the friend set replacing those agents having the worst trust or capability to provide suggestions. Therefore, the goal of the algorithm is to minimize $D_a$ during several *epochs*. The period of time between two consecutive epochs is equal to a pre-fixed value $T$.

The algorithm described below, called *Friendship and Group Formation* (FGF), implementing the previously described scenario, is an adaptation of the Users-to-Groups (U2G) algorithm presented in [20], but differently from it the FGF adopts the social capital $SC$ as optimization function.

At each epoch, the FGF algorithm executes two tasks, the former is the *active task* which runs each time that $a$ sends its requests to the other agents, while the other task, named *passive task*, provides to manage the requests coming from the other agents. More in detail:

### 5.1. Active task

This task is composed by the following steps (see Figure 1):

1. The set $Best_a = \bigcup_{\rho \in C} BC_a^\rho \bigcup BR_a$ is computed.
2. A friendship request is sent by $a$ to $b$ for each agent $b \in Best_a - F_a \bigcup_{g \in G_a} g$.
3. If $b$ accepts the friendship request then it is added to $F_a$. Furthermore, if $b \in BC_a^\rho$, then the agent $k \in F_a$, $k \notin Best_a$ that has the worst trust value $trust(k, \rho)$ is removed from $F_a$. Otherwise, if $b \in BR_a$, then the agent $k \in F_a$, $k \notin Best_a$ that has the worst value of A-REL(k) is removed from $F_a$.
4. If $b$ does not accept the friendship request, the set $GROUP_b$, formed by all the groups having $b$ as a member, is required from the agent $a$ to the $DF$. Then, for each group $g \in GROUP_b$, the disadvantage $D_a^*$ deriving if the group $g$ is computed by the agent $a$ and added to $G_a$ (see Formula 2). If $D_a^* < D_a$, then an affiliation request to $g$ is sent by $a$ to $g$.
5. If $g$ accept the affiliation request of $a$, then $g$ is added to $G_a$. Furthermore, if $b \in BC_a^\rho$, then the agent $k \in F_a$, $k \notin Best_a$ that has the worst trust value $trust(k, \rho)$ is removed from $F_a$. Otherwise, if $b \in PR_a$, then the agent $k \in F_a$, $k \notin Best_a$ that has the worst value of A-REL(k) is removed from $F_a$.
6. If $g$ does not accept the affiliation request sent by the agent $a$, then a *call for a new group* is sent by $a$ to all the agents belonging to $F_a \bigcup_{g \in G_a} g$.
7. When some agent agrees with the call for a new group, then such a group is created and registered to the DF.

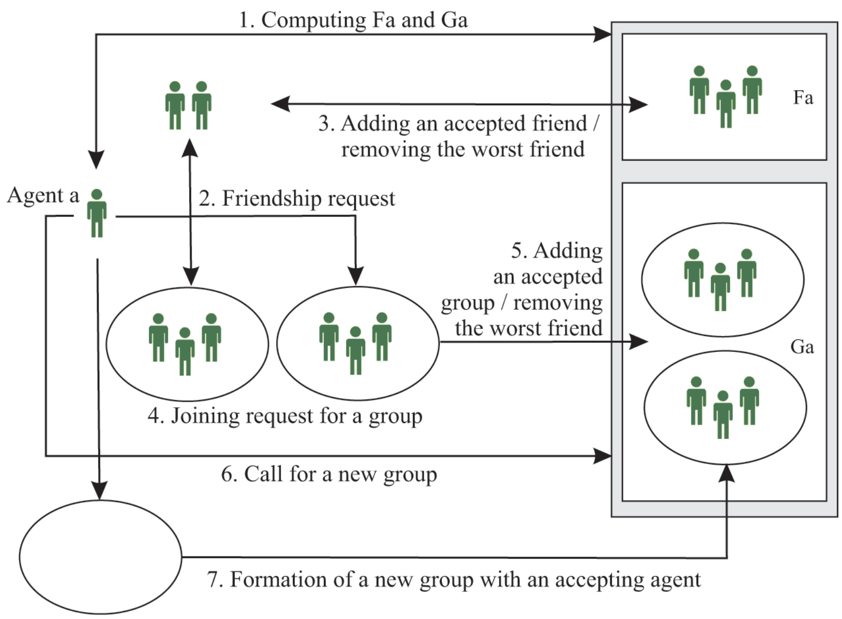


Figure 1: The active task of an agent.

To summarize, the agent $a$ executes the *Active task* for having the friendship or the presence in a group $G_a$ of those agents that belong to $Best_a$ but not yet to $F_a \bigcup_{g \in G_a} g$. To this aim, firstly $a$ requires the friendship of each missing agent $b$. Then, if the missing agent $b$ does not accept the friendship, $a$ requires to affiliate itself with some group where $b$ is present. If any of these groups do not accept the affiliation request, then $a$ tries to form a new group with agents that have needs similar to $b$. In this way, $a$ hopes to attract $b$ in a next future.

### 5.2. *Passive task*

This task is composed by the following steps (see Figure 2):

1. $a$ accepts a friendship request coming from $b$ only if the insertion of $b$ in $F_a$ implies a decrement of the disadvantage $D_a$. Recall that when a new agent is inserted in $F_a$, then it is necessary to remove another agent on the basis of the rules described in step 3 of the *Active task*.
2. When the administrator of a group $g$ that contains $a$ receives a affiliation request coming from an agent $b$, it activates a voting procedure that involves all the agents affiliated with the group $g$. Votes can be positive or negative. The vote is positive if the insertion of $b$ in the set $F_a$ implies a decrement of the disadvantage $D_a$. If only the majority of the votes is positive, then the affiliation request of $b$ is accepted. Also in this case, the inclusion of $b$ in $g$ requires the removal of another agent on the basis of the rules described in step 3 of the active task.
3. If an agent $b$ sends call for a new group, then $a$ will accept the affiliation proposal with the new group if the affiliation of $b$ to $F_a \bigcup_{g \in G_a} g$ does not increase the disadvantage $D_a$.

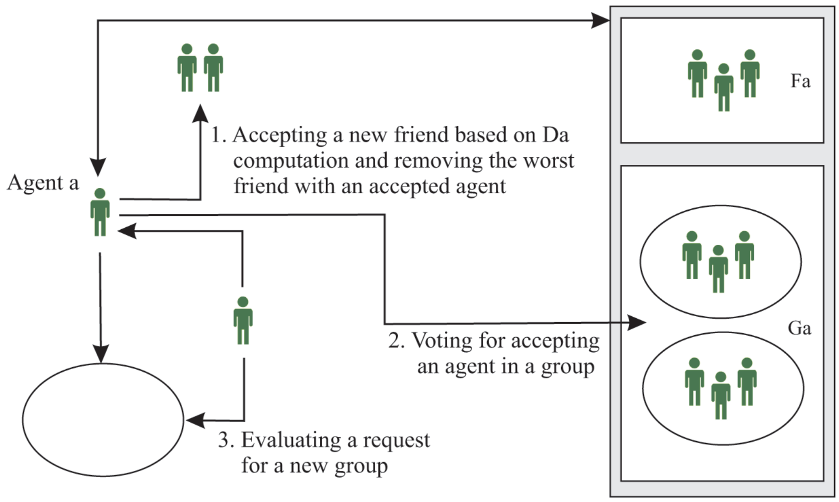

Figure 2: The passive task of an agent.

In other words, the goal of this task is to manage the friendship requests coming from other agents and, similarly, the affiliation requests that other agents send to groups where $a$ is affiliated with.

## 6. Theoretical results

The reference scenario described in Section 3 can be seen as a non cooperative game [18] involving the $N$ IoT agents belonging to the set $A$, where each agent of $A$ tries, at each step of the competition, to increase its own *bank amount* $B_a = 1 - D_a$.

We define *Social Capital* $SC$ of an internal MAS organization based on friendships and groups:

**Definition 1.** *Social Capital.*

$$SC = \frac{\sum_{a \in A} B_a}{\|A\|} \tag{3}$$

$SC$ is the *average advantage* associated with a MAS or, in detail, the mean value of all the contributions $B_a$ given by each agent $a$.

Each agent $a_i$ is associated with a set of possible strategies $S^i = \{s^i_1, s^i_2, .., s^i_{n_i}\}$, where each strategy $s_i$ is a set containing $k$ agents to be contacted for friendship, $l$ agents to be contacted for recommendations and $h$ groups to join with[2].

If each agent $a_i$ chooses a strategy $s^i_k \in S^i$, then we have a *profile* $\mathbf{s} = \{s^1_{k_1}, s^2_{k_2}, .., s^N_{k_n}\}$.

We call *payoff* of $a_i$ associated with the profile **s** the mapping $U_i(\mathbf{s})$, that represents the utility for the agent $a_i$ associated with the adoption of the profile **s**. In our scenario, $U_i(\mathbf{a})$ is equal to the bank amount $B_i = 1 - D_i$, where the disadvantage $D_i$ computed by formula 2.

[2]Clearly the values of $k, l, h$ will depend on the particular strategy $s_i$

From the game theory, we say that a profile $\overline{\mathbf{s}} = \{\overline{s}^1, \overline{s}^2, .., \overline{s}^N\}$ is a Nash equilibrium if, for each agent $a_i$ we have:

$$U_i(\overline{s}^i, \overline{\mathbf{s}}^{-i}) \geq U_i(s^i_j, \overline{\mathbf{s}}^{-i}) \qquad \forall s^i_j \in S^i \tag{4}$$

where $\overline{\mathbf{s}}^{-i}$ indicate the strategies of the other N-1 agents.

Therefore, if the profile $\overline{s}$ is a Nash equilibrium, each agent $a_i$ prefers the action $\overline{s}^i$ to each other, supposing each other agent $a_w$ plays $\overline{s}^w$, with $w \leq N$. In other word, any agent is not motivated to move from the profile $\overline{s}$.

In this section, we supply a few relevant results achieved by the FGF algorithm. First, we show that FGF reaches the aim of building relationships among agents that contribute to the growth of the global social utility. In other words, we prove that at each iteration of the FGF, the social capital $SC$ does not decrease.

**Lemma 1.** *The social capital $SC$ does not decrease at each new iteration of the FGF algorithm.*

**Proof 1.** *At each iteration, the only actions performed by each agent $a$ can be either* i*) increasing $B_a$, if some best contributor (or recommender) accepts its affiliation request or* ii*) not updating $B_a$, if there are not agents accepting its affiliation request. However, due to actions performed by other agents, $B_a$ can decrease with the removal of a favorite contributor or recommender from $F_a$ or from a group belonging to $G_a$. Furthermore, let $b$ be a best contributor or recommender with respect to a category $\rho^*$ that removes itself from $F_a$ or from a group belonging to $G_a$. In this case, the disadvantage $D_a$ will increase due to the necessity to replace $b$ with the best existing alternative $b^\circ$ and, in this way, the corresponding increment will be $trust(b, \rho^*) - trust(b^\circ, \rho^*)$, that results to be lesser than 1. However, $b$ removes itself from $F_a$ or from a group belonging to $G_a$ only if $a$ is not one of its favorite contributors or recommenders, in such a way the removal implies a decrement of $D_b$ equal to 1. Overall, the sum of $D_a$ and $D_b$ will decrement of 1-$((trust(b, \rho^*) - trust(b^\circ, \rho^*))$. From this later, it is possible to directly derive that at each iteration the sum of all the agent disadvantages decreases and, consequently, the sum of all the contributions $(1 - D_a)$ increases. This proves the theorem.*

Then, we can prove the following theorem 1.

**Theorem 1.** *The FGF algorithm converges to the optimal social capital.*

**Proof 2.** *The proof directly derives from the Theorem 1 proved in [20], that guarantees the convergence of the algorithm U2G, having the same behaviour of FGF, but different optimization function, that in the case of FGF is the social capital SC. The proof of the convergence of the algorithm is valid in the case the optimization function is monotonically non decreasing. Combining this result with the previous lemma, assuring the non-decreasing monotonicity of the social capital produced during the execution of the algorithm, we obtain the stated result.*

Now, we also provide the notion of *merit* $\eta_a^\rho$ of an agent to feature the global trustworthiness, with respect to the category $\rho$, that an agent $a$ has from its whole community.

**Definition 2.** *The merit $\eta_a^\rho$ of an agent $a$ in the category $\rho$ can be assumed to be the number of agents that consider $a$ as the best contributor or the best recommender.*

Furthermore, we provide also the notion of *expected gain* of an agent $a$, which characterizes the increment that $a$ expects of its bank amount at a given step of the competition. By denoting $P_a(x)$ as the probability distribution of the bank amount increment for $a$, i.e. the probability of an increment equal to $x$ of the bank amount, we have obtain:

**Definition 3.** *The expected gain $\delta_a$ of the agent $a$ is defined as the expected value of the probability distribution $P_a(x)$.*

Finally, we consider valid the following assumption, named *mirror assumption*:

**Assumption 1.** *Let $a$, $b$ be two agents, such that at a given iteration is $\eta_a^\rho < \eta_b^\rho$. In this case, the number $Nu_a$ of users contacting $a$ for a service request falling in the category $\rho$ will be lesser than the number $Nu_b$ of users that, for the same reason, contact $b$.*

This assumption appears reasonable given that if $\eta_a^\rho < \eta_b^\rho$, then the global satisfaction of the agent community due to the performances of $a$ is lesser than the satisfaction received for the performances of $b$. Since the global satisfaction of the agent community is based on feedback received from the users, it is reasonable to assume that in such a situation also the users will prefer to contact $a$ instead of $b$. In other words, this assumption means that in a specular way the users' choices reflect the agents' choices. This will be particularly true if the trustworthiness of $a$, represented by the number of agents considering $a$ as a favorite interlocutor, actually is able to capture the expertise of $a$. Consequently, the more the agents trust models are built strictly on the basis of the users' feedback, similarly to the case of the trust model presented in Section 4, the more the mirror assumption can be considered as valid. Moreover, the more the adopted trust model is able to capture the actual agents expertise, the more the assumption above fitting the real situation. This assumption leads us to proof the following second result:

**Theorem 2.** *At each iteration, for each pair of agents $a$, $b$ such that $\eta_a^\rho < \eta_b^\rho$, the expected gain $\delta_a$ will be lesser than the expected gain $\delta_b$.*

**Proof 3.** *Let $a$, $b$ be two agents, such that at a given iteration $\eta_a^\rho < \eta_b^\rho$. Assuming as valid the mirror assumption, then the number $Nu_a$ of users contacting $a$ for a service request falling in $\rho$ will be lesser than the number $Nu_b$ of users contacting $b$. Furthermore, in this case, the probability $PI_a$ that $a$ can be contacted by other agents for providing a contribution or a recommendation, always referred to $\rho$, will be lesser than the corresponding probability $PI_b$ and, consequently, the expected number of the agents $Ni_a$ that will contact $a$ for the same reason will be lesser than the expected number $Ni_b$ of those contacting $b$. Analogously, the expected number of agents $No_a$ contacted by $a$ in the category $\rho$ is greater than the expected number of agents $No_b$ contacted by $b$, due to the high probability that the expertise of $a$ is smaller than that of $b$. Thus, also assuming for sake of simplicity that both a contribution or recommendation price is equal to $p^*$ then, when the current interaction will end, the expected gain $\delta_a$ will be $Nu_a \cdot p + Ni_a \cdot p^* - No_a \cdot p^*$, that results smaller of the corresponding expected gain $\delta_b$ for the agent $b$.*

| Agent | F | G |
|---|---|---|
| $a_1$ | $\{\,\}$ | $\{\,\}$ |
| | $\{\,\}$ | $\{a_2\}$ |
| | $\{a_2\}$ | $\{\,\}$ |
| | $\{a_2\}$ | $\{a_2\}$ |
| $a_2$ | $\{\,\}$ | $\{\,\}$ |
| | $\{\,\}$ | $\{a_1\}$ |
| | $\{a_1\}$ | $\{\,\}$ |
| | $\{a_1\}$ | $\{a_1\}$ |

Table 1: All the possible configurations of *friend agents* and *groups*.

Finally, we can proof the following third result:

**Theorem 3.** *The configuration of strategies computed by the FGF algorithm when the convergence is reached corresponds to a Nash equilibrium.*

**Proof 4.** *Reaching the configuration of friendships and groups associated with the convergence of the FGF algorithm, it is impossible for any agent $a$ to unilaterally perform actions that lead to increase its $B_a$, if all the other agents remain in the same convergence configuration. In fact, each agent $a$ can try to increase $B_a$ only by substituting some friendship or joining group requests present in its strategy in the convergence configuration with other ones more advantageous in terms of bank amount. However, if the other agents remain in the convergence configuration, the new requests will not be necessarily accepted and $a$ might decrease its bank amount. Therefore, $a$ too is rationally motivated to remain in the convergence configuration. This situation exactly corresponds to the definition of Nash equilibrium.*

## 7. Two examples

In this section, we present and analyze two examples of scenarios used to test our FGF algorithm. Suppose we have a set of IoT agents $A = \{a_1, a_2\}$ and a set of categories $C = \{\rho_1, \rho_2\}$. In both examples, we consider all the possible configurations of *friend agents* and *groups* for each agent (see Table 1). The values of $t_S$ (threshold for the computation of best contributors) and $t_A$ (threshold for the computation of the best recommenders) are fixed respectively as 0.4 and 0.7. We report the details the two examples below:

**Example I**. In the first case, the two agents have complementary values of expertise. In particular, $a_1$ and $a_2$ have respectively the following expertise for each category: $e_{a_1}(\rho_1) = 0.4$ and $e_{a_1}(\rho_2) = 0.8$; $e_{a_2}(\rho_1) = 0.7$ and $e_{a_2}(\rho_2) = 0.4$. Moreover, the measures of trust for the two agents are the following: $trust_{a_1}(a_2, \rho_1) = 1$ and $trust_{a_1}(a_2, \rho_2) = 0.1$; $trust_{a_2}(a_1, \rho_1) = 0.02$ and $trust_{a_2}(a_1, \rho_2) = 0.8$. We define also the values of suggested reliability: A-REL$(a_1) = 0.8$ and A-REL$(a_2) = 0.7$.

Recall that, in order to obtain the maximum performances, the agents would have – in their set of friends – or in some group with which they are affiliated with – only the agents belonging

| Agent | BC | BR |
|---|---|---|
| $a_1$ | $BC_{a_1}^{\rho_1} = \{a_2\}$ <br> $BC_{a_1}^{\rho_2} = \{\}$ | $BR_{a_1} = \{a_2\}$ |
| $a_2$ | $BC_{a_2}^{\rho_1} = \{\}$ <br> $BC_{a_2}^{\rho_2} = \{a_1\}$ | $BR_{a_2} = \{a_1\}$ |

Table 2: (Example I) The sets of $\rho$-best contributors and of best recommenders.

| Agent | F | G | D |
|---|---|---|---|
| $a_1$ | $\{\,\}$ | $\{\,\}$ | 1 |
| | $\{\,\}$ | $\{a_2\}$ | 0 |
| | $\{a_2\}$ | $\{\,\}$ | 0 |
| | $\{a_2\}$ | $\{a_2\}$ | 0 |
| $a_2$ | $\{\,\}$ | $\{\,\}$ | 0,8 |
| | $\{\,\}$ | $\{a_1\}$ | 0 |
| | $\{a_1\}$ | $\{\,\}$ | 0 |
| | $\{a_1\}$ | $\{a_1\}$ | 0 |

Table 3: (Example I) The disadvantage for all configurations of *friend agents* and *groups*.

to the sets of $\rho$-best contributors and best recommenders (see Equation 1). In this case, it is clear that for obtaining the maximum performances, the optimal sets for the two agents are $\bigcup_{\rho \in C} BC_{a_1}^{\rho} \bigcup BR_{a_1} = \{a_2\}$ and $\bigcup_{\rho \in C} BC_{a_2}^{\rho} \bigcup BR_{a_2} = \{a_1\}$. This assertion is supported by Table 2, where the sets of $\rho$-best contributors and best recommenders for each agent are shown. For the agent $a_1$, the set of $\rho_1$-best contributors is $BC_{a_1}^{\rho_1} = \{a_2\}$ because $a_2$ has the highest value of expertise and a trust value greater than the fixed threshold $t_S$. Also, the set of *best recommenders* is $BR_{a_1} = \{a_2\}$ because $a_2$ has the highest suggested reliability value and this one is greater than the fixed threshold $t_A$. We can make similar considerations for the agent $a_2$.

Now, we carry out an analysis to understand what is the global configuration, obtained by the combination of those shown in Table 1, that allows us to achieve the maximum value of *social capital* (see Equation 3). We will show that FGF will select, among all the possible configuration, just that one optimizing the global social utility.

In Table 3, we report the disadvantage that each agent obtains in the single configuration, while in Table 4 we report all the possible configurations that are consistent with the symmetry of the relations *friendship* and *joining with a group*. In particular, if $a$ is a friend of (resp., is in the group $g$ with) $b$, then also $b$ is a friend of (resp., is in the group $g$ with) $a$.

In this example, the maximum value of SC is equal to 1 and FGF chooses just one of the three configurations having such a value.

**Example II**. In the second case, the two agents have opposite values of expertise. In particular, $a_1$ and $a_2$ have respectively the following expertise for each category: $e_{a_1}(\rho_1) = 0.9$ and $e_{a_1}(\rho_2) = 0.8$; $e_{a_2}(\rho_1) = 0.2$ and $e_{a_2}(\rho_2) = 0.1$. This means that $a_1$ has the highest

| Global configuration | $a_1$ | $a_2$ | SC |
|---|---|---|---|
| I | $\{\ \}\ \{\ \}$ | $\{\ \}\ \{\ \}$ | 0,1 |
| II | $\{a_2\}\ \{\ \}$ | $\{a_1\}\ \{\ \}$ | 1 |
| III | $\{\ \}\ \{a_2\}$ | $\{\ \}\ \{a_1\}$ | 1 |
| IV | $\{a_2\}\ \{a_2\}$ | $\{a_1\}\ \{a_1\}$ | 1 |

Table 4: (Example I) The values of SC for the global configurations.

| Agent | BC | BR |
|---|---|---|
| $a_1$ | $PC_{a_1}^{\rho_1} = \{\}$<br>$BC_{a_1}^{\rho_2} = \{\}$ | $BR_{a_1} = \{\}$ |
| $a_2$ | $BC_{a_2}^{\rho_1} = \{a_1\}$<br>$BC_{a_2}^{\rho_2} = \{a_1\}$ | $BR_{a_2} = \{a_1\}$ |

Table 5: (Example II) The sets of $\rho$-best contributors and of best recommenders.

value of *merit* in both categories. Moreover, the measures of trust for the two agents are the following: $trust_{a_1}(a_2, \rho_1) = 0.001$ and $trust_{a_1}(a_2, \rho_2) = 0.03$; $trust_{a_2}(a_1, \rho_1) = 0.9$ and $trust_{a_2}(a_1, \rho_2) = 0.8$. We define also the values of suggested reliability: A-REL$(a_1) = 0.8$ and A-REL$(a_2) = 0.2$.

The same assumptions have been carried out here as in the previous example. For this reason, we show directly the sets of $\rho$-best contributors and of best recommenders in Table 5, and the values of disadvantage for all configurations of *friend agents* and *groups* in Table 6.

In this example, the maximum value of SC is equal to 0.55 and FGF chooses just this configuration. We also note that the algorithm, choosing this configuration, rewards the agent with the highest value of *merit*. In this way, FGF ensures that $a_1$ does not cooperate in any way with $a_2$ that has low values of expertise in both categories.

## 8. Experiments

In order to evaluate the proposed approach, we performed a certain number of simulations aimed at verifying that the application of the algorithm described in Section 5 leads to optimize the value of the Social Capital for the considered community of IoT agents. To this aim, we designed a simulator which has been implemented in Octave/Matlab language[3]

We simulated a community of 1000 IoT agents, that we imagine to operate in a smart city, and which can have different levels of expertise. As each step of the simulation the following tasks are executed:

- a certain number of interactions among agents is simulated; for each interaction, a feedback is released to the agent counterpart;

[3]The simulator is currently available at the following address: http://globus.dmi.unict.it/ fmessina/exp.m

| Agent | F | G | D |
|---|---|---|---|
| | $\{\,\}$ | $\{\,\}$ | 0 |
| $a_1$ | $\{\,\}$ | $\{a_2\}$ | 1 |
| | $\{a_2\}$ | $\{\,\}$ | 1 |
| | $\{a_2\}$ | $\{a_2\}$ | 1 |
| | $\{\,\}$ | $\{\,\}$ | 0,9 |
| $a_2$ | $\{\,\}$ | $\{a_1\}$ | 0 |
| | $\{a_1\}$ | $\{\,\}$ | 0 |
| | $\{a_1\}$ | $\{a_1\}$ | 0 |

Table 6: (Example II) The disadvantage for all configurations of *friend agents* and *groups*.

| Global configuration | $a_1$ | $a_2$ | SC |
|---|---|---|---|
| I | $\{\,\}\ \{\,\}$ | $\{\,\}\ \{\,\}$ | 0,55 |
| II | $\{a_2\}\ \{\,\}$ | $\{a_1\}\ \{\,\}$ | 0,5 |
| III | $\{\,\}\ \{a_2\}$ | $\{\,\}\ \{a_1\}$ | 0,5 |
| IV | $\{a_2\}\ \{a_2\}$ | $\{a_1\}\ \{a_1\}$ | 0,5 |

Table 7: (Example II) The values of SC for the global configurations.

- information about mutual trust among agents are updated as described in Section 4.
- the algorithm FGF (Section 5) is simulated for all the agents of the community.
- the value of the disadvantage is recorded for all the agents of the community.

The reader may refer to Table 8 for the description of the relevant parameters (and their values) used for the experimental trials.

In particular, we categorized the agents as those having a *low level of expertise*, i.e. those agents that, in average, have a level of expertise smaller than $0.5$, and agents having a *high level of expertise*, i.e. those agents that, in average, have a level of expertise greater than $0.5$. For simplicity, agents of the first category are called *low performance* agents, while the latter are called *high performance* agents. Therefore, each time an interaction between two agents is simulated, the feedback is generated according to the level of expertise of the agent that provided the service.

As premised at the beginning of this section, the aim of our experiments is to illustrate by a simple simulation how the FGF algorithm is capable to lead the community to high and stable values of Social Capital. To this end, as reported in Table 8, we performed the experiments with different values of parameters $Rl$ and $Rh$, which represent the ratio of low performance agents and the ratio of high performance agents, respectively. Clearly, it is $Rh = 1 - Rl$, as also indicated in Table 8.

Results are reported in Figure 3, which shows the values of Social Capital computed on the entire community, at the end of each time step of the simulation. The several curves differ

Table 8: Experiment parameters

| Parameter | Meaning | Values |
|---|---|---|
| N | number of nodes of the community | 1000 |
| NG | initial number of groups | 50 |
| $t_S$ | threshold for the best contributors | 0.6 |
| $t_A$ | threshold for the best recommenders | 0.6 |
| $\alpha$ | weight the reliability in the computation of trust | 0.5 |
| Rl | Ratio of agents holding a low level of expertise | $[0.2 - 0.8]$ |
| Rh | Ratio of agents holding a high level of expertise | $1 - Rl$ |
| AVG($f_{Rl}$) | Average value of generated feedback for low performance agents | 0.2 |
| AVG($f_{Rh}$) | Average value of generated feedback for high performance agents | 0.8 |

for the value of the ratio $Rl$ (see Table 8), which span from $0.2$ to $0.8$. We can observe that, when $Rl \in \{0.7, 0.8\}$, the measured Social Capital is lesser than that measured when $Rl \in \{0.2, 0.4, 0.6\}$. The relevant fact is that, as expected, the execution of the FGF algorithm leads to the asymptotic convergence of the Social Capital toward the values $0.7$ ($Rl = 0.2, 0.4, 0.6$) and $0.8$ ($Rl = 0.7, 0.8$).

Finally, as the values of the Social Capital are calculated on the different values of the disadvantage, we measured the bias around the measured values of the disadvantage, to verify whether it assumed acceptable values. To this end, we computed the values of the Coefficient of Variation (CV), i.e. the ratio between the standard deviation and the mean of the disadvantage for all the values $Rl = \{0.2, 0.4, 0.6, 0.7, 0.8\}$. Results are reported in Figure 4, which shows values around $10\%$.

## 9. Conclusion

In a smart city environment based on an IoT infrastructure, introducing a suitable organization inside a community of self-interested agents associated with the IoT devices, allow agents to cooperate for increasing their individual capabilities of providing services to users. Some of the approaches proposed in the past face this problem by trying to maximize either the profits of the single actors or the profit of the whole community. Nevertheless these kind of approaches may lead to a few negative effects: first of all, deceptive or fraudulent behaviors may occur if the goal of the considered approach is of rewarding the most aggressive agents; moreover, introducing a sort of social flattening which is not capable to reward the different merits of individual agents since, in the case, the proposed approach is mainly focused on optimizing the profit associated with the whole community.

In this paper we have proposed an approach aimed at maximizing a certain measure – called social capital – for the whole community, by using an objective function depending on the trust

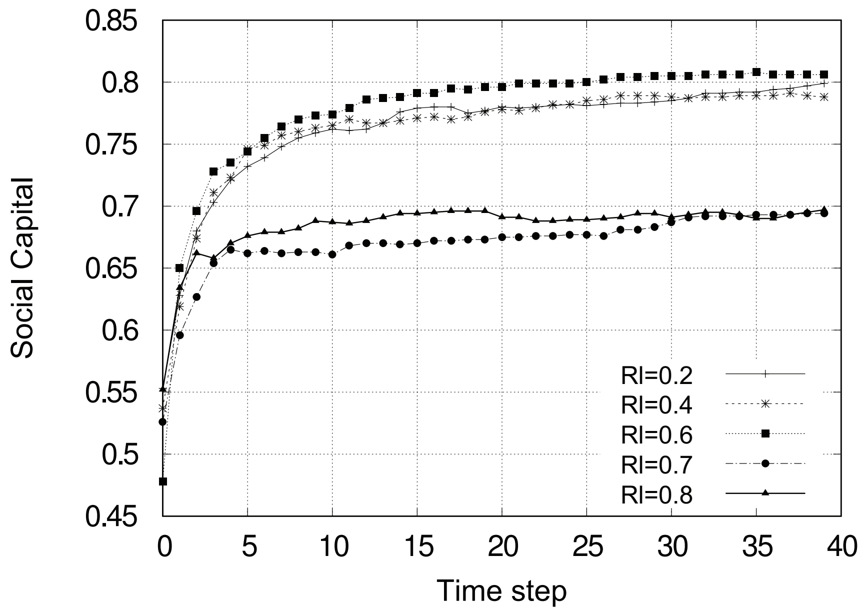


Figure 3: Values of Social Capital during the simulation

relationships occurring among agents by considering friends and groups formed within the community. The approach includes an algorithm – called FGF – to form friendship and groups. By this approach, those IoT agents that are perceived as the most trustworthy are rewarded by our approach, in such a way it is possible to introduce a form of meritocracy into the community. We have provided a number of theoretical results related to the demonstration that the FGF algorithm converges to the optimal social capital and that the meritocracy is assured. In particular, we have proved that the solution computed by the FGF algorithm corresponds, in a game theory perspective, to a Nash equilibrium. A number of numerical simulations confirmed the theoretical results.

It is important to here highlight that the approach we have introduced has a practical impact on an IoT system in a smart city context, providing the possibility of realizing groups of IoT objects collaborating with each others for improving the social capital of the IoT community, also assuring to each individual object that its personal income will be the maximum obtainable in an intelligent community, provided with a meritocratic mechanism.

Our ongoing research is expected to test the FGF algorithm in complex contexts, mainly characterized by the presence of a large agent community where there are large sets of agents, and in real cases where agents really operate on the behalf of human users. More in detail, the development a real application in the domain smart city services is in an advanced planning phase; it appears as a promising opportunity for introducing a suitable organization in the smart city service system and profitable test our approach.

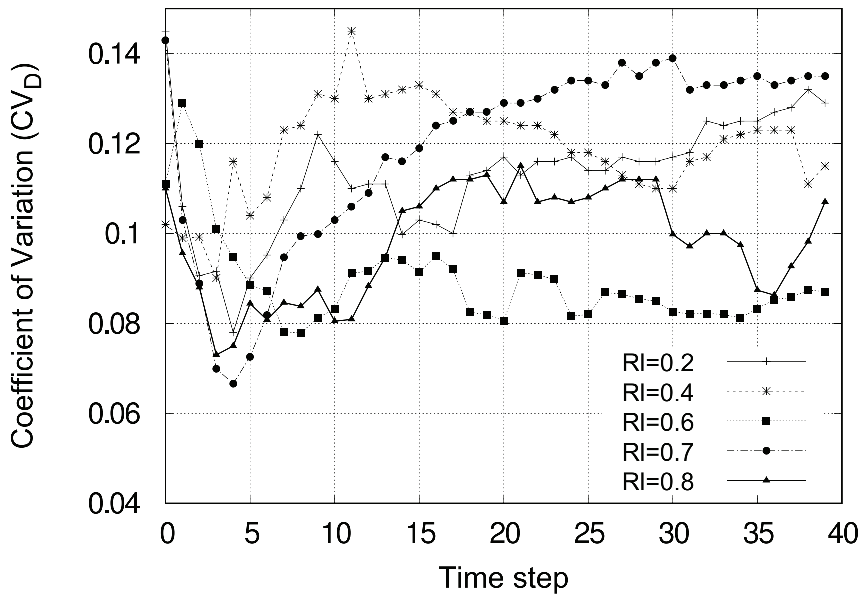


Figure 4: Values of Coefficient of Variation of the disadvantage D ($CV_D = \frac{STD\_DEV(D)}{AVG(D)}$)

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