Goal-based Multi-agent Collaboration Community Formation: A Conceptual Model

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Abstract

Multi-agent systems mostly consist of self-interested agents, which behave selfishly to achieve their goals. However, their limited capabilities and knowledge, environment's constrained resources and shared goals lead them to a collaborative goal achievement process. Based on previous findings, assuming fixed organizational structures is not practical solution for dynamic multi-agent systems. Therefore, agents need to acquire an understanding of the other agents' goals and policies, update their current perception of their environment constantly and form/reorganise an effective community for any instances of a collaboration process.

This paper summarizes a Collaboration Community Formation Model (CCFM) introduced in [Golpayegani *et al.*, 2016] in a conceptual level. This model describes the fundamental structural elements of a dynamic collaborative community. We also introduce an agent model which describes agents' internal components that allows agents to model their dependencies using goal reasoning and self-organise their collaboration community and select their potential collaborators amongst the numerous agents in the system.

1 Introduction

Multi-agent collaboration is a coordinated behaviour in which a collaboration community is formed and members negotiate to achieve a mutually accepted stance and cooperate to fulfil their shared goal [Grosz and Kraus, 1999]. As an example, in congestion management, vehicles may collaborate to achieve better throughput at junctions [Dusparic and Cahill, 2009], or in residential energy demand management system, households may collaborate to make better use of low cost energy during the off-peak hours. [Golpayegani *et al.*, 2015].

Collaboration community formation is dependent on the multi-agent system's organization. A multi-agent system organization can be defined using agents' individual and collective behavioural and structural characteristics. These characteristics, such as agents' relations, roles, policies, intentions and goals determine the behaviour of the systems and the organizational structure of its elements [Horling and Lesser, 2004]. A successful collaboration process requires an effective community of agents which are willing to engage in the process. However, fixed organizational structures such as hierarchies and holarcies are not practically applicable as multi-agent systems are mostly embedded in dynamic environments. Dynamic organization formation such as coalition formation, teamwork and self-organizations are the approaches that have been used in such environments.

Coalition is a goal-directed and short-lived group of agents in which participants increase their utility by working together and helping each other to perform tasks that a single agent cannot carry out by itself [Shehory and Kraus, 1998]. Coalitions are formed to increase the utility of every single self-interested individual agent during a cooperating process. Coalition formation approaches mostly focus on maximizing the individual utilities of the agents in the coalition. It is claimed that the effectiveness of these coalitions is not affected by the arrangements of the other existing agents in the systems [Rahwan *et al.*, 2012]. However, they do not address agents collaboration for shared goal achievement, when agents may have conflicting goals that may affect their collaboration community organization.

Team is an organization of cooperative agents working together towards a shared goal. Team members coordinate their actions and cooperate to maximize the team's utility [Tambe *et al.*, 1999]. A team is a specific form of collaboration where team members do not have any individual goals, or their goals are a subset of shared goal. In teamwork approaches the focus is on role assignment and task distribution to the participating agents to achieve a shared goal [Nair and Tambe, 2005]. However, generally, most agents have individual goals that may conflict with the shared goal in some circumstances. This makes the collaboration process challenging, as agents should find a balance between fulfilling their individual and shared goals.

Self-organisation is a paradigm that enables agents to adapt their structures to the changes in their environment or requirements without any external control [Serugendo *et al.*, 2006]. Such adaptation includes forming a new structure (e.g., collaboration community) or rearranging the existing structure to meet the requirements. Self-organisation have been used in many existing works such as team formation [Hoda *et al.*, 2010] and emergent planning [Picard *et al.*, 2005], to form suitable networks and structures of agents for cooperation purposes. For example, the DIET platform [Hoile *et al.*, 2002] enables agents cooperatively exchange information and rearrange their structure according to the changes in their requirements. However, it does not use self-organisation for collaborative goal achievement process.

There are a number of reasons why a dynamic collaboration community formation is essential in multi-agent systems; firstly, in a dynamic multi-agent system where agents can join and leave a system, it is not possible to consider a definite structure as it is a non-deterministic environment. Secondly, having a shared goal and suitable capabilities are necessary factors for community formation. However, they are not sufficient, since agents' individual goals and policies may conflict with others in certain timesteps. Moreover, a lot of existing work (e.g., [Rahwan *et al.*, 2009; Michalak *et al.*, 2010]) assumes that all the agents in the environment are the potential collaborators and they have to share their states and information whether or not they are willing to engage in a collaboration process. This assumption affects the efficiency of collaboration, as agents share information with agents that might not be eager to collaborate.

The rest of this paper is organised as follows: Section 2 introduces the Agent Model and briefly reviews CCFM. The experiment design is presented in Section 3 and the results are discussed in Section 4. The conclusions and future work are discussed in Section 5.

2 Multi-agent Collaboration

Limited knowledge, complicated tasks, constrained resources and shared benefits or goals are some of the reasons for agents to cooperate. Agents' cooperation for achieving a shared goal is called collaboration. For a successful collaboration, agents need to prioritize their goals, form an effective collaboration community and coordinate their behaviour to achieve the shared goal. The effective collaboration community consists of agents with a shared goal or agents with shared benefit (e.g., their individual goal achievement depends on others shared goal achievement). In a dynamic system where agents' organisation cannot be pre-designed, finding collaborators and forming an effective community is challenging [Golpayegani, 2015]. To address these issues, this paper describes the following models: a conceptual model of the previously proposed Collaboration Community Formation Model (CCFM) supported with a new self-organising design for agents. Applying these two models, agents can reason about their neighbours' goals and changes in their environment to form effective communities.

2.1 Agent Model

Agents should be able to autonomously make their decisions and take actions towards their goals (e.g., individual and shared goals). They also need to constantly update their perception of the environment as it changes frequently. For example, they need to be aware of changes in the availability of the resources they depend on or the other agents that they may need to interact with. To address these issues, we considered three main structural blocks for the agents in our model: Self-organising Unit, Goal Relation Type Model and

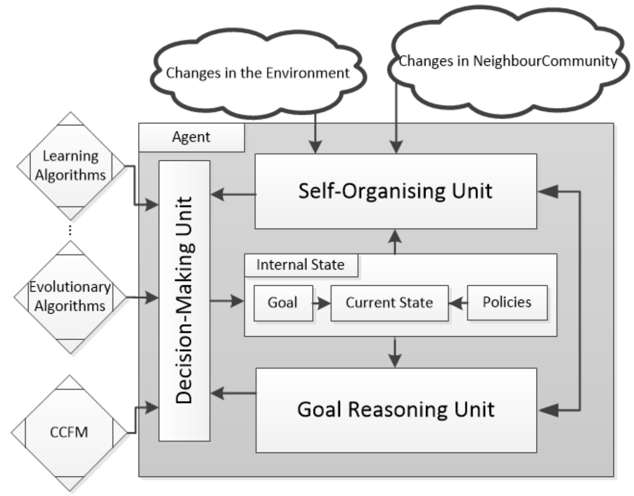

Figure 1: Agent Model

Decision-Making Unit. These blocks are depicted in Figure 1 and described as follows.

Self-organising Unit

Self-organising Unit enables agents to adapt their mental model (e.g., the overall understanding of their surrounding) to the changes in their environment and communities. These adaptations reflect on their goal and policy rearrangement and action selection process, which happens in the Decision-Making Unit. This unit manages agents mental model of the environment including agent's communities and the members of those communities. It updates this model when a new agent joins the community or a member leaves. When an agent joins the community for the first time, the self-organising unit has to build a mental model by interacting with the community members.

Goal Reasoning Unit

Each agent holds a Goals' Relation Type Model (GRTM), which stores its goals' relations with other agents in the same community. These relations include any conflicts, overlaps, precedence dependencies that each agent's goals might have with others. GRTM helps the agent to find proper collaborators for each collaboration process considering their goals' relations. For example, if the collaborating agents have conflicting goals their collaboration will not be successful. Agents identify their goals' relation types based on their goals and policies and current states.

Decision-Making Unit

Agents decide what community to join, necessary actions to take to achieve goals and whether to collaborate or not. They may use different artificial intelligence algorithms such as learning [Dusparic *et al.*, 2013], evolutionary or collaborative approaches [Golpayegani *et al.*, 2016] to find an optimal solution. In this paper we specially focus on collaborative approaches that agents decide about their next actions individually and collaborate if the shared goals are not achievable.

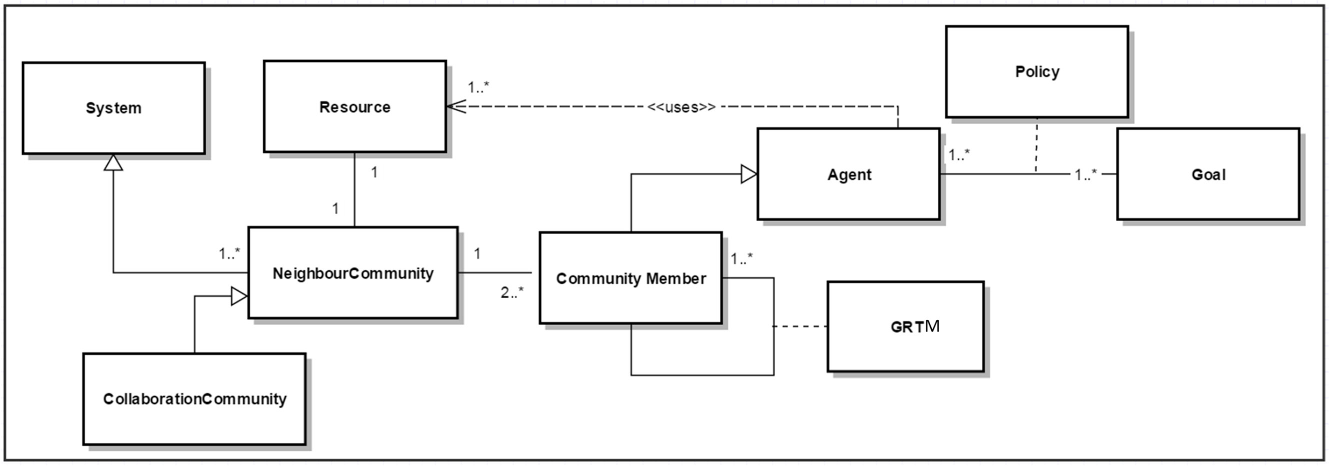

Figure 2: Conceptual Model for CCFM

2.2 Collaboration Community Formation Model

CCFM enables agents to find the most related collaborators and form an effective collaboration community. CCFM's conceptual model captures the fundamental structural elements of a dynamic system where agents initiate their collaborative processes. As depicted in Figure 2, each system has at least one NeighbourCommunity which is associated with a single resource. NeighbourCommunity composed of agents (Community Member) which share a resource. Each Community Member can join or leave a community at any time during its lifetime and it can be the member of more than one community. Agents broadcast their state when they join/leave a community and other Community Members update their GRTM.

The collaboration initiator agent (e.g., could be any of the agents in the NeighbourCommunity that identifies the need for collaboration to achieve a shared goal) nominates a group of possible collaborators. It uses its GRTM and sends collaboration requests to those which have overlapping or dependent goals, if they do not have conflicting goals or policies. It then waits for time t to receive acknowledgements. The agents which have received a collaboration request either accept or reject it, considering their current state, individual goals and policies. Finally, the collaboration community will be formed with the agents which agreed to collaborate.

3 Experiment Design

This experiment evaluates the performance of CCFM using smart-grid scenarios. The aim of this evaluation scenario is to compare the performance of a selfish approach and a cooperative approach and CCFM which tries to balance the selfishness and level of cooperation. Settings as follows:

- A team-based approach where agents try to achieve the team's goal and subsequently their individual goals have a lower priority. In this approach, all the agents in a $NeighbourCommunity$ which use the same resource are team members.
- The CCFM approach where agents try to balance their selfishness and level of cooperation using CCFM. In this scenario, if the shared goal is not achievable with the individually decided actions, a $CollaborationCommunity$ will be formed based on agents' AGMs, GRTMs and the $NeighbourCommunity$.
- The P-MCTS approach where agents maximize their own utilities by achieving their individual goals. In this approach, agents take their individual actions independently.
- We have also included the results from a Greedy approach as a baseline, in which agents neither form any specific organizations nor use any artificial intelligence and act selfishly to achieve their goals.

These scenarios are simulated using GridLAB-D, which is a power network simulator developed by the US Department of Energy [Chassin *et al.*, 2008].

3.1 CCFM in Smart Grid Scenario

Energy demand is unevenly distributed over a day, depending on households' consumption. It usually increases in the morning and peaks in the evening (when people get ready to leave their houses and when they get home), and the off-peak hours starts from mid-night. The maximum demand determines the grid's available capacity for the whole day. If demand increases during peak hours, the utility companies turn on more generators, which is costly. Load balancing and shifting it from peak hours to off-peak hours is an approach to decreasing cost for companies and end-users. The smart-grid scenario was chosen because it can include both selfish and cooperation characteristics in agents (representing electrical devices), when they interact with each other within a system (representing the grid). Additionally, different types of goals and dependencies can be covered.

The scenario covers a community of 90 houses with an EV for each house, in a neighbourhood served by a single transformer. The energy usage in each house is categorised into two types: the base load, which is the normal energy consumption of electrical devices, and reschedulable load, which is an EV's consumption (battery charging) that can be coordinated with other EVs' consumption over the grid. Each EV might have a different daily plan (leaving and arriving time) and journey length. EVs coordinate their consumption through collaboration to achieve their individual goals and shared goal(s) simultaneously. EVs require an average of 6 hours to be sufficiently charged to meet their individual goals, and 10 hours to be charged 100%. This community has 10 Emergency EVs (EEVs) (e.g., local doctor's vehicle) and 80 regular EVs. An EEV starts charging as soon as it gets back home. The normal EV tries to get enough charge for the next journey and minimize its cost by maximizing off-peak time consumption, when low cost energy is provided. EVs self-organise their consumption plans according to the changes in the grid's capacity and their neighbours charging plans). The shared goal is to minimize the overload times and to balance the demand over the peak and off-peak hours. It incentivises EVs with low cost energy during off-peak hours.

In this scenario, 350 KW is selected as 85% of actual grid capacity. In a real setting, experts adapt it according to predicted consumptions. The system's (including EVs and EEVs) goal is to reduce peak usage.

Action Selection

EVs can choose ON or OFF as their actions in each timestep (e.g., 15 minutes). In all of the approaches mentioned, EVs individually calculate their best actions using a best first search method called Monte Carlo Tree Search (MCTS) which has been shown to improve agents action selection performance [Golpayegani *et al.*, 2015]. In the P-MCTS approach, EVs do not coordinate but take individual actions. In the team-based approach, EVs coordinate their actions if their collective set of actions would not allow the shared goal (the transformer load would exceed a certain threshold) to be fulfilled. In CCFM, both individual and shared goals are considered during the community formation as oppose to in team-formation where the shared goal is all that matters. For example, if the transformer load exceeds its threshold when 10 EVs and 5 EEVs have decided ON as their next actions, the CCFM invites the EVs and allows the EEVs to achieve their goals while the team-based approach will consider all 15. However, regards to EEVs individual goal they should not be stopped charging as they have be charged as soon as possible.

Collaboration Need Identification

Variation of base load demand results in variations of available capacity in the grid. At each timestep, if the collective demand from EVs cannot be handled by the available capacity in the grid, the shared goal will not be achieved. EVs know the constraint (the maximum available load) and the other EVs in their $NeighbourCommunity$ that want to use the same resource for the coming timestep. As an example, if the transformer capacity is 80 EVs for the next timestep and 85 EVs have decided to use electricity, this will result in transformer overload (shared goal failure). Therefore, the initiator EV explores its GRTM and invites the related EVs and forms the collaboration community.

Parameter Settings

According to CCFM, there are a number of parameters that should be set for EVs in this smart-grid scenario. Each EV/EEV has a minimum State of Charge (SoC) that must have depending on its travel distance. In this case, we consider 60% of SoC for EVs and 100% for EEVs. The maximum amount of SoC is 100%. EVs current SoC is the parameter that EVs use to decide to accept or reject a collaboration request. EVs consider their policy about charging in off-peak times, their SoC, next journey length, and remaining time until next journey and decide to accept or reject the collaboration request accordingly.

3.2 Performance Criteria

Performance is measured using the following metrics:

- The smoothness of the load curve is calculated using Peak-to-Average Ratio (PAR), which shows the distribution of demand over time (the lower the PAR is the better demand distribution is achieved).
- The number of times the transformer is overloaded, which shows the shared goal fulfilment.
- The number of times EVs run out of charge, which shows the fulfilment of EVs' individual goals.
- The number of EEVs that could not achieve their individual goals, which shows how the algorithms behave with conflicting goals.
- The SoC's standard deviation for EVs, which shows the fairness of the algorithms.

4 Results

The transformer load depicted in Figure 3 shows the results obtained from four different approaches and baseline over three days. The Greedy approach increases the demand during peak time as both EEVs and EVs start charging as soon as they get back home. In this approach EEVs' goals and one of the individual goals of the EVs (e.g., get enough charge for the next journey) is fulfilled. However, the shared goal (e.g., load balancing and shifting the demand to off-peak times) and one of the individual goals of EVs (e.g., minimizing the charging costs) are not fulfilled.

In the P-MCTS approach, EVs and EEVs find their charging plans individually. EVs and EEVs' individual goals have priority over the shared goal. This approach has partially utilised the off-peak times by shifting some part of the EVs' demand to the off-peak times. However, because EVs do not coordinate their actions they could not achieve the shared goal since they are overloading the transformer at peak times (see Figure 3 and Table 1). In the team-based approach, based on the shared goal (e.g., minimizing the number of overload) all EEVs and EVs formed a team and cooperate to achieve the shared goal.

As shown in Figure 3, the team-based approach has the best results for demand shifting and load balancing goals(e.g., number of transformer Overload = 0 in Table 1). However, as reported in Table 1, many of the EEVs have not achieved

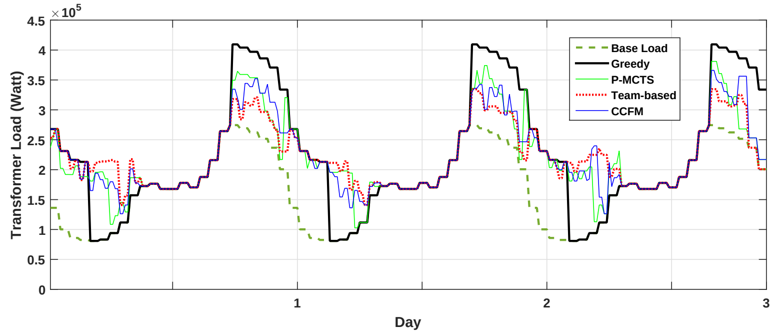

Figure 3: Transformer load results for different approaches

their individual goals. In other words, in the team-based approach, the shared goal has the highest priority. In the CCFM approach, both shared goal and individual goals are considered and at each timestep, EVs form a community and make the best decision. In this approach, EEVs cannot participate in the collaborations as their goal is dependent on the shared goal, with Precedence Dependency.

The demand load from CCFM is higher than team-based and lower than P-MCTS during peak hours (see Figure 3). This is because it allows the EEVs to achieve their goals in peak-times and shifts the EVs demand to off-peak times as EVs try to achieve the shared goals and their individual goals simultaneously.

As recorded in Table 1, the PAR results show that the team-based approach has achieved the smoothest transformer load. This implies that it has achieved the load balancing and demand shifting goals better than CCFM and the P-MCTS approach. Additionally, these figures show that CCFM achieves better results than the P-MCTS approach as it has minimized the number of EVs charging during the peak times and shifted their uncritical demands to off-peak times.

The team-based approach can be considered as a fully co-operative approach (achieving the shared goal in all 3 days, which is the transformer overload = 0), while the P-MCTS approach is a selfish approach (all individual goals are fulfilled, which is EVs' SoC is never less than 0). CCFM has balanced the selfishness of agents and their level of cooperation as it has overloaded the grid fewer times than the P-MCTS approach and most of the individual goals are met.

Additionally, the reported standard deviation of EVs' SoC (STDEV), shows that P-MCTS and CCFM have a fairer distribution of SoC for EVs. This can be explained by their community formation algorithm. In the P-MCTS approach all the agents can have the same share of grid's capacity, as they do not care about the load balancing and demand shifting goals. In CCFM, EVs' current state along with their individual goals and policies determines if they should collaborate or continue and take their previously decided actions. On the other hand, the team-based approach allows EVs to take their actions while they do not have any conflicts with the shared goal and it does not distinguish between agents with different SoCs.

5 Related Work

In multi agent systems' community, the idea of community formation has been studied in the context of coalition formation [Rahwan *et al.*, 2009] and team formation [Tambe *et al.*, 1999].

A lot of existing work in coalition formation assumes that there is a fully connected static structure of the community where all agents know each other and can communicate with each other [Rahwan *et al.*, 2009; Michalak *et al.*, 2010; Ramchurn *et al.*, 2010]. However, in dynamic environments such as open systems, considering all the agents in the environment as possible collaborators is not practical, as agents leave and join communities frequently. Additionally, finding effective collaborators needs a large number of communications. To decrease the number of communications between agents, some approaches have introduced a neighbourhood community, which consists of agents that are potential collaborators [Ye *et al.*, 2013]. However forming a fixed neighbourhood in open systems is not a practical solution.

Abdallah [Abdallah and Lesser, 2004] introduces a coalition formation approach based on underlying organization structure, which is used to guide agents during their coalition formation. An organization's structure is a domain knowledge, which clarifies the agents' relationships, conflicts and dependencies. Such knowledge is not achievable in dynamic systems where agents leave and join the system frequently.

Team formation depends on agents' goals and capabilities and the knowledge of formation process [Nair and Tambe, 2005].

Tambe [Cohen and Levesque, 1991] introduces a team architecture called STEAM, based on joint intentions framework and SharedPlans theory [Grosz and Kraus, 1999]. The joint intentions framework explains agents' reasoning about joint commitments and shared goals. SharedPlans discusses the reasoning about joint plans, intentions and beliefs. The combination of these two theories in STEAM can ensure the consistency of beliefs for all team members. However, it does not address the team's goal's fulfilment when the team members have their individual desires to pursue. Decker [Decker and Lesser, 1992] introduces a framework called Generalized Partial Global Planning (GPGP), which forms teams more dynamically compared to STEAM. In GPGP, agents have several alternative ways to fulfil a specific goal, which is pos-

Table 1: Experimental Results

		Statistical Analysis				
		PAR	Transformer Overload	EV SoC $\leqslant 0$	EEV SoC <100	STDEV
Day 1	P-MCTS	1.66	12	0	0	6.61
	Team-based	1.45	0	4	3	24.78
	CCFM	1.59	5	3	0	6.35
Day 2	P-MCTS	1.78	11	0	0	6.67
	Team-based	1.51	0	0	4	24.78
	CCFM	1.55	4	0	0	6.75
Day 3	P-MCTS	1.76	13	0	0	6.88
	Team-based	1.49	0	3	4	19.40
	CCFM	1.63	9	0	0	6.84

sible because they can alternate between a set of individual plans. Each sub-goal, which is associated with a plan, can affect other agents in the system. These effects are realized after a number of interactions. Agents build an internal model based on their interactions' effects gradually and use it during team formation. This model clarifies how a plan can affect and be affected by others. Although this approach is dynamic and considers the agents' relationships based on their actions, plans and goals, it does not address the interrelationship between agents' individual goals and shared goals.

6 Conclusion and Future work

This paper briefly reviewed a Collaboration Community Formation Model (CCFM) supported by an Agent Model which includes agents' internal structural components. It addressed the community formation problem where agents collaborate to fulfil their individual goals and shared goals simultaneously. It enables agents to find a balance between selfishness and level of cooperation by considering their current state.

This research can be expanded in several directions: The Agent Model and GRTM can be integrated with the goal model in GPGP [Decker and Lesser, 1992] to include agents' alternative plans, when conflicts occur during the collaboration. Additionally, CCFM can be expanded to enable agents to initiate multiple collaboration processes in the same timestep.

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