Emergence of Multiagent Coalition by Leveraging Complex Network Dynamics

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Abstract. Emergence of a single coalition among self-interested agents operating on large scale-free networks is a challenging task. Existing approaches, both centralized and decentralized, suffer from high overhead costs to maintain network wide communiation. Furthermore, these works start by assuming a pre-established static complex network platform and then employ agents on the nodes of the network for mutual interactions. In other words, agents do not have the capability to form the network. These approaches use a given structure of the complex network with fixed properties and do not explore the other possible network configurations by varying the topological features. In addition to this, they do not use the network dynamics to control the dynamics of agent interactions. In this paper, we present a decentralized game-theoretic approach to this single coalition emergence problem that limits agent communications only to their immediate neighbors. We enable the agents to choose their interaction partners to form a dynamically growing SF network and show that this network formation process facilitates that emergence phenomenon. We perform an extensive computational study by varying some topological properties over two models of the scale-free network. The novel insight that we gain is that by increasing degree-heterogeneity and clustering-coefficient, implemented through agents' partner selection strategy, we could enhance the likelihood of the emergence of a sustained single coalition over various types of scale-free networks.

Keywords: Scale-free network, emergence, complex network dynamics, multiagent coalition, game theory

1 Introduction

There has been a great deal of interest in the multiagent systems (MAS) community about the emergence and maintenance of coalitions among agents [1–4]. A coalition is defined as a group of agents who have decided to cooperate in order to perform a common task. However, in the interaction of selfish agents, where defection actions bring more short-term benefit, emergence of sustained coalitions becomes challenging. For example, in solving distributed combinatorial problems such as in resource and task allocation and MAS planning and scheduling every agent tries to maximize its own good without concern for the global good. Traditionally this problem has been modeled as a Prisoner's Dilemma (PD) game [5] within a game-theoretic framework. The PD game, where selfish and rational agents try to maximize their utility by interacting with each other, offers a powerful metaphor for understanding how cooperation may emerge in the face of short-term selfish behavior. When it is played iteratively among two agents, the "tit-for-tat" strategy has been shown to maximize cooperation [6]. Although defection is the only evolutionary stable strategy in iterated PD [7], the likelihood of cooperation is remarkably increased if the agent interaction is constrained by the underlying network topology [8–10]. The emergence of cooperation has initially been shown over a simple grid topology [5] and later for complex networks such as scale-free (SF) [9] and small-world [11] networks. However, in these approaches agents do not use the network dynamics to enhance the emergence phenomenon. These works start by assuming a pre-established static complex network platform and then employ agents on the nodes of the network for mutual interactions. In other words, agents do not have the capability to form the network. These approaches use a given structure of the complex network with fixed properties and do not explore the other possible network configurations by varying the topological features. Therefore, the results that they generate is specific to the respective network topologies. In addition to this, they do not explore how the topological insights could reinforce agent dynamics to control the collective phenomena of cooperation. Therefore, while these help us to understand which network configurations favor cooperative behavior, agents do not seem to leverage the dynamical properties of the network. Moreover these works do not intend to achieve **full cooperation**.

In this paper, we present a decentralized *coalition emergence* approach where self-interested agents in a MAS operating on large SF networks exploit the complex network dynamics to facilitate the convergence into a single coalition. We use an iterated PD game to capture the agent interactions. As most real-world networks display both degree-heterogeneity and high-clustering and few previous studies have explored such networks, we also investigate the coalition emergence process over a high-clustering model of the SF network. We develop a computational model to study how our algorithm performs on various types of SF networks by varying the degree-heterogeneity and the clustering coefficient. Our goal is to determine the topological insights that could be embedded into the agent dynamics for successful emergence of a single coalition where agents all over the network cooperate with each other **The novelty of our approach lies in the fact that, unlike the previous works that assume pre-established static networks, we enable the agents to choose their interaction partners to form a dynamically growing SF network and show that this network formation process enhances that emergence phenomenon**.

The remainder of this paper is organized as follow. We first discuss the relevant literature in section 2 followed by a description of the two network models for studying the dynamical properties of the SF network. Then we present our decentralized coalition emergence approach in section 3. We provide an extensive computational study in section 4 and finally conclude with a summary of our observations and discussion of future work in section 5.

2 Related Works

Salazar et al. [1] use a single coalition emergence approach for achieving full cooperation in a MAS. Using Axelrod's tribute/tax framework [12], they develop a centralized leader based coalition formulation model over complex networks where the agents pay an amount of tax to the leaders in order to join a coalition. They have shown that their distributed information sharing consensus mechanism effectively reduces the tax rate imposed by the leader. However, both the leader tax collection and information sharing require maintenance of networkwide multi-hop communication which would incur overhead cost. Moreover, they do not investigate the variation of topological features and its impact on their algorithms, and consider the underlying network as a pre-established, fixed configuration and static platform.

The challenges of the emergence of cooperation in MAS are intrinsically related to the the problem of convergence of a social convention. Social convention is a category of norms that involves coordination among the agents and is considered for the analysis of cooperation problems [11]. The emergence of social norms in a MAS has been extensively investigated in eclectic fields. In [11], a pure coordination game and two simple action-update rules are used to show convergence to a MAS social convention over highly clustered small-world and low-clustering SF networks. They consider a MAS consisting of N agents that can choose one out of two states: A or B; and a social convention is reached if all of the agents are in one of the two states. The cost for reaching consensus is based on the average number of links per node, and is shown to be lower in complex networks. It, however, focuses only on the diameter of the graph as the key parameter to determine the efficiency of convergence.

The social learning model [13] is one where agents learn strategy from repeated interaction with multiple agents. Although it explores heterogenous learning policies for a population of agents, and consider neighborhood size and selection criterion, the underlying topology that it considers is restricted to grid. To expand the scope of social learning, [14] uses two social instruments, viz. rewiring and observation, to enhance the emergence of convention. The social instruments enable the agents to "observe" whether they are in any subconventions and to use "rewiring" to break it through topological reconfiguration and achieve full convergence. The "rewiring" instrument, however, performs better in low-clustering societies which limits the scope of its applicability.

To overcome the limitations of rewiring, [15] adopts an alternative technique to have global view of the state of the system. A hierarchical clustering scheme is introduced where a coordinator in each cluster recommends convention for its cluster. Leveraging the hierarchical structure, the inconsistencies among the different coordinators are resolved. The random hierarchical cluster formation scheme, however, does not take into account the effect of underlying topological constraints and the cost of communication between the coordinator and the cluster members.

A parallel thread of research involves studies by physicists on the issue of cooperative behavior among selfish agents over structured complex networks in the framework of evolutionary game theory. [9] shows that the growth and preferential attachment rule of the SF network significantly enhances the cooperative behavior. [10] studies the impact of average degree on the outcome of the PD game played over SF, small-world and random networks. The effect of high clustering to enhance cooperation over the SF network has been studied in [16] where each node plays a PD game with its neighbors.

The above research, conducted by various disciplines, emphasize on the fact that addressing various topological issues of complex network for enhancing the cooperation is as important as formulating appropriate interaction strategies for the agents. Hence the organization of cooperation and the evolutionary dynamics of the PD game can greatly be enhanced by leveraging the knowledge of network theory.

2.1 Network Models

We choose to build the interaction topology as a SF network model [17]. It is an ideal platform for implementing MAS because its node degree follows the power-law distribution independently of the scale of the network, a feature suitable for large-scale MAS. Also the SF structure is robust against self mutation and environmental perturbation. Therefore, the intended cooperative behavior in a large-scale MAS is expected to benefit from the SF topology. The standard Barabasi-Albert(BA) SF network model [17], however, suffers from low clustering. Moreover, the heterogenous degree-distribution of the BA model is fixed by the constant power law scaling-exponent. In the context of social systems and in many real world applications we observe that the network exhibits both node degree-heterogeneity and high clustering. Hence, to emulate more realistic scenarios, unlike [1, 15], instead of treating a SF network as a fixed-configuration and static topology, we consider variations of the dynamical properties of the network.

In the following we describe the two SF network models that we use to build a computational model for studying the performance of our approach and to gain insights about the impact of topological features over the process of coalition emergence:

BA Model

The degree distributions of the BA SF model [17] follows a power-law form $p(k) \sim k^{-\gamma}$ for a large k, where $p(k)$ is the probability that a node is connected to k other nodes with $\gamma = 3$. It is formed as follows:

(i)Growth: Starting from m_0 nodes, at every time step a new node is added with m ($m <= m_0$) edges which connect between the new node and m different previously existing nodes.

(ii) Preferential Attachment: A node i is chosen to be connected to the new node according to the probability $\prod_{n \to i} = \frac{A+k_i}{\sum_j (A+k_j)}$ where k_i is the degree of node i and **A** is a *tunable parameter* representing the initial attractiveness of each node.

The scaling-exponent γ in the power-law degree distribution is given by $\gamma = 3 + \frac{A}{m}$, where $-m < A < -\infty$. The average degree by construction is equal to *2m*, and is independent of A. The heterogeneity of the degree distribution and the clustering coefficient is strongly affected by A. For the BA model, $A = 0$ that restores the fixed exponent $\gamma = 3$. By increasing the value of A, both the heterogeneity of degree distribution and the scaling exponent (γ) could be increased that results in increasing clustering coefficient.

For a very large SF network, the clustering coefficient of this model is close to zero at $\gamma = 3$. Since many real-world networks possess both high clustering and SF properties, we would use an extended model of a SF network with tunable clustering coefficient.

Extended BA Model

The extended model [18] follows the growing process of BA model that starts with m_0 nodes. At every time step a new node i is added to the network and gets connected with m ($m <= m_0$) of the previously existent nodes. The first link of node i is added to node j of the network (with $j < i$) following the preferential attachment rule of the BA model. The remaining $m - 1$ links are added in two different ways: (a) with clustering probability p the new node i is added to a randomly chosen neighbor of node j and (b) with probability $(1 - p)$ node i gets connected to one of the previously existing node using the preferential attachment rule again.

This procedure ensures a degree distribution of $p(k) \sim p^{-\gamma}$ with a tunable clustering coefficient. With $p = 0$, the extended model transforms to the regular BA model with low clustering coefficient (at $\gamma = 3$). For values of $p > 0$, the clustering coefficient increases monotonously. Since this model partially follows the preferential attachment rule of the BA model (the first link of each new node is added through preferential attachment rule), the heterogeneity of the degree distribution of the extended BA model can also be controlled by A.

3 Decentralized Coalition Emergence

We develop a decentralized coalition emergence approach that does not require the existence of a leader for a single coalition to emerge and sustain. According to our approach, agents need to communicate only with their immediate neighborhood to form a coalition. We assume that agents are self-interested and have bounded rationality. Instead of considering a fixed configuration topology, we assume that the MAS interaction network grows over time. In the beginning we enable the agents to form the network by choosing their interaction partners dynamically. The network consists of N agents where every agent is embedded on a node of the network. The adjacent agents (within single-hop distance) are defined as the *neighbors*. Every agent is equipped to play an *n-person* iterated

PD game with each one of its neighbors and their interactions are represented by the network links. The agents starts playing the PD game after the network is formed and we consider the network as a closed system. After each round of the game, the payoff for each agent gets accumulated. We assume that every agent knows the accumulated payoff of its immediate neighbors. Agents can execute any one of the two interaction strategies: to cooperate (C) or to defect (D). The payoff generated from each game is defined by the payoff matrix in Table 1:

Table 1. Payoff Matrix for the Prisoner's Dilemma Game

	C	D
C	(3,3)	(0,5)
D	(5,0)	(1,1)

We consider the accumulated payoff to be one of the criteria to join/form coalition. But a simple payoff based coalition emergence strategy does not always lead to the formation of a single coalition. Hence, in addition to the neighborhood payoff information, we enable the agents to use network based knowledge such as the coupling strength (CS) of the nodes to form the coalition. There are various definitions of CS [19] of the nodes in a network, each defined according to the goal of the respective works. We define the CS of an interacting node based on its social influence which is represented by its degree [20]. We argue that the social status or the CS of a node can influence its neighbors to join its coalition. Each node in the network determines its CS as following: $CS_i = \frac{k_i}{M}$ where k_i is the degree of node i and M is a pre-defined large number (e.g., Avogadro constant).

According to this definition, agents with high-degree bear large coupling strength and are in a position to induce greater influence over other agents to form coalition. But that does not guarantee that an agent with smaller coupling strength that joins a coalition could attract its neighbors with larger coupling strength to join its coalition. Hence solely coupling strength based coalition formation scheme does not always guarantee the emergence of a single coalition. To circumvent this problem, we define the parameter *accumulated coupling strength*(ACS) in which whenever a new node i joins another node j in a coalition, its coupling strength gets increased by the addition of the coupling strength of j with which it has coupled: $ACS_i = CS_i + CS_j$, where node j either belongs to a coalition or is an independent agent with higher payoff and $CS_i <= CS_j$.

Every agent gets an increment in its coupling strength as it joins a coalition. Therefore, even though initially only nodes with large coupling strength could form a coalition with its comparatively low coupling strength neighbors, as the game proceeds their coupling influence is propagated and expanded towards the boundary of the coalition with the increase of the member accumulated payoffs. Thus the combined effect of high accumulated coupling strength and higher accumulated payoff attracts more agents to join the coalition. As a result, the coalition monotonically grows in size until all the agents converge into a single coalition.

```
Algorithm 1: NetworkFormation
Require: m_0 initial nodes
Require: number of edges (m) of the newly
connected node: m ≤ m_0
1. setInitialAttractiveness() = A;
2. setClusteringProbability() = p;
3. implementBAModel(GOTO lines 4-5);
        OR
   implementExtendedBAModel(GOTO lines 6-9);
4. WHILE(m ≤ m_0)
5. {linkToNode(i): ∏_{n→i} = (A+degree_i)/(∑_j (A+degree_j));}
6. linkToNode(i): ∏_{n→i} = (A+degree_i)/(∑_j (A+degree_j));
7. WHILE(m ≤ m_0 − 1)
8. {linkToNeighborOfNode(i)withProbability(p);
9. linkToNode(i)withProbability(p-1):
       ∏_{n→i} = (A+degree_i)/(∑_j (A+degree_j));}
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```
Algorithm 2: InitialCoalitionFormation
Require: Coupling strength and payoff is transparent
only to immediate neighbors
Require: All the agents are Independent
1.  networkFormation();
2.  randomStrategySelection(all agents);
3.  playPDGamewithNeighbors();
4.  IF (PayOff(a) < PayOff(b) AND
5.     CouplingStrength(a) ≤ CouplingStrength(b))
6.  {
7.  JoinCoalition(b);
8.  incrementCouplingStrength(a);
9.  }
10. ELSE (IndependentAgent(a))
```

Network Formation: In the beginning agents choose their interaction partners and form the network as described in Algorithm 1. Agents are enabled to set the values of their initial attractiveness parameter (A) and the clustering probability (p). Agents may either form the network according to the BA model (lines 4-5) or may use the extended BA model (lines 6-9). In the BA model, all the links (m) of the new node are connected to the existing nodes using the

Algorithm 3: Decentralized Coalition Formation Algorithm

Require: Coupling strength and payoff is transparent only to immediate neighbors

```
1.  initialCoalitionFormation();
2.  playPDGamewithNeighbors();
3.  IF (CoalitionAgent(a) AND !Disconnected(a))
4.  {
5.  IF (PayOff(a) < PayOff(b) AND
6.        CouplingStrength(a) ≤ CouplingStrength(b))
7.     IF (!IndependentAgent(b))
8.        {
9.        JoinCoalition(b);
10.       incrementCouplingStrength(a);
11.       }
12.    ELSE IF (IndependentAgent(b))
13.       {
14.       FormCoalition(b);
15.       incrementCouplingStrength(a);
16.       }
17. }
18. IF (CoalitionAgent(a) AND Disconnected(a))
19. {
20. IndependentAgent(a);
21. resetCouplingStrength(a);
22. }
23. IF (IndependentAgent(a))
24. GOTO lines 5-16;
25. mutation();
```

preferential attachment rule (line 5). On the other hand, in the extended BA model only the first link of the new node is added using the preferential attachment rule (line 6). The remaining links of the new node ($m_0 - 1$) are added to the randomly chosen neighbors of the first neighbor of the new node with the probability p (line 8) or using the preferential attachment rule with the probability *p-1* (line 9). By varying the value of A, the degree-heterogeneity of the resultant network can be controlled and p determines the clustering level of the extended BA model. Using a computational model described in section 4, we determine how the agents should set these two topological parameters such that the resultant network enhances the emergence of a single coalition when agents form coalitions using algorithms 2 and 3.

Agent Roles: An agent can take one of the following two roles: (a) be a coalition member if it belongs to a coalition or (b) be an independent agent if it remains outside the coalitions.

Game Initiation: Algorithm 2 depicts how initial coalitions are formed at the beginning of the game. Every agent starts out as an independent agent and there is no coalition. Agents choose their interaction strategy randomly and generate the payoff according to the payoff matrix in Table 1 by playing a *n-person* PD game with its neighbors (lines 2-3). Suppose that the strategy seeking agent is a and its maximum payoff neighbor is b. Agent a forms a coalition (according to lines 4-7) and increases its coupling strength by adding the coupling strength of b to its own (line 8). Intuitively agents with larger degree would generate higher payoff in the first shot of the game and hence would act as the seed for the coalition formation process. After the first round, there would be multiple coalitions. The number of coalitions will depend on the size of the network. There would be some independent agents as well whose payoff/coupling strength might be higher in their neighborhood and hence they would not join any coalition (line 10).

The Interaction Strategies: Similar to [1], in our algorithm each agent in a coalition acts as a cooperator with its own coalition agents in the neighborhood, and defects with the rest. An independent agent takes the interaction strategy that the majority of its neighbors adopted in the previous round.

Coalition Strategies: At the beginning of every round each agent plays the PD game and employs the coalition strategies to join/leave/switch or form coalition according to Algorithm 3. The algorithm is executed from agent a's perspective. a could be a coalition member or an independent agent. Its maximum payoff neighbor b either belongs to a different coalition or is an independent agent. At first agent a checks whether it belongs to a coalition and is not physically disconnected from its coalition (line 3). After this condition is met agent a checks whether its payoff is less than its neighbor b's payoff and its coupling strength is less than or equal to b's coupling strength (lines 5-6), then agent a joins b's coalition if b is not an independent agent (lines 7-11). If b is an independent agent, then agent a forms a coalition with it (lines 12-16). In both cases agent a increments its coupling strength (lines 10 and 15).

If agent a does not have any one-hop link to other members of its coalition then it is considered to be disconnected from its coalition. In this case (line 18), agent a becomes an independent agent and resets its coupling strength to the original value (lines 20-21).

Agent a could be an independent agent (line 21) in which case it either joins b's coalition or forms a coalition with b according to lines 5 - 16.

Mutation: In order to allow the agents to explore the state space, they are enabled to mutate with a certain probability. Through mutation a coalition member could leave its existing coalition and could become an independent agent by resetting its coupling strength. An Independent agent changes its interaction strategy via mutation.

4 Computational Model and Results Analysis

We use a computational model to conduct extensive simulations for our coalition emergence approach by varying the degree-heterogeneity and the clustering coefficient of the BA and the extended BA model. We increase the value of the initial attractiveness parameter (A) in order to increase the degree-heterogeneity of the network and increase the value of the clustering probability p (used in the extended BA model) to have high-clustering; and observe the convergence of the coalitions. Heterogeneity is measured by the standard deviation of the degree distribution.

4.1 Simulation Setup

Our network consists of 1000 agents represented as nodes in the SF network. A link between two nodes of the network indicates that the agents interact and play the PD game. To implement the BA model, we initially form a small mesh network consisting of ten nodes and then add each new node according to the preferential attachment rule of the BA model. We set the default minimum node degree as 10 in both models ($m = 10$). As a consequence, each new node gets connected to at most 10 existing nodes. The value of M that is used to define the coupling strength of the nodes is set to 1000.

To implement the extended BA model, we vary the values of p which is the clustering probability of a new node to get linked to a randomly chosen neighbor of the high degree node with which it is initially connected (as described in the Related Works section).

All the results reported are averages over 500 realizations for each network for different values of the network parameters (e.g., degree-heterogeneity, clustering coefficient etc.). Each simulation consists of 1000 time steps where a time step refers to a single run of the program. The mutation rate is set to 0.2.

4.2 Simulation Results

BA Model

Low-Clustering and Small Heterogeneity: To observe the performance of our coalition emergence approach over a low-clustering SF network, we set the initial attractiveness parameter A = 0. Simulation result shows that among the 500 realizations of the network, there are sixty-three instances at which multiple coalitions emerge (see Table 2). The average global clustering coefficient for this configuration is 0.08468 that indicates the clustering is low.

Large Heterogeneity: In order to investigate the impact of large heterogeneity, we gradually increase the value of the initial attractiveness parameter A from 0 to 700. In Figure 1 we observe that as the value of A increases, the likelihood of convergence into a single coalition increases. We also notice that increased heterogeneity improves the quality of convergence with the increase of the clustering of the network (see Table 2). Therefore, we see that if the agents choose their interaction partners using a large value of their initial attractiveness parameter ($A > 0$), the resultant network with large heterogeneity in the degree-distribution would increase the likelihood of the emergence of a single coalition.

From the study on the BA model we observe that our coalition emergence approach performs well when the network clustering coefficient is high (see Table 2).

Table 2. BA & Extended BA Model: Instances of sustainable multiple coalitions (#MC), the average Global Clustering Coefficient (GCC) and the average Degree-Heterogeneity (DH) over 500 realizations of the network for various values of p and A.

	BA Model			Extended BA Model					
	p = 0.0			p = 0.2			p = 0.4		
A	#MC	GCC	DH	#MC	GCC	DH	#MC	GCC	DH
0	63	0.08468	19.36	150	0.1079	19.81	110	0.1305	20.18
10	16	0.11152	22.8	38	0.12364	22.25	92	0.1394	21.86
20	8	0.16094	28.65	29	0.15484	25.07	118	0.1580	23.69
30	7	0.21248	30.49	44	0.18406	27.40	147	0.1746	25.17
40	3	0.25872	33.37	73	0.21077	29.41	155	0.1894	26.49
50	5	0.3002	36.07	86	0.23345	31.09	182	0.2020	27.63
80	3	0.40262	41.21	124	0.29042	35.24	221	0.2320	30.37
100	1	0.45496	45.24	133	0.32023	37.47	211	0.2479	31.86
200	0	0.6238	55.1	192	0.41918	45.45	186	0.3029	37.41
300	0	0.7177	61.85	192	0.47809	50.86	200	0.3381	41.28
500	0	0.8209	70.95	172	0.54811	58.06	187	0.3827	46.67
700	0	0.88	76.50	168	0.58879	62.92	172	0.4097	50.33
	Extended BA Model								
	p = 0.6			p = 0.8			p = 1.0		
A	#MC	GCC	DH	#MC	GCC	DH	#MC	GCC	DH
0	155	0.154		140	0.178	21.24	135	0.20	22.23
10	141	0.1576	21.67	135	0.18116	21.46	134	0.1998	21.60
20	161	0.1674	22.77	134	0.18004	22.04	89	0.19818	21.88
30	160	0.1764	23.68	104	0.18248	22.91	52	0.19544	22.31
40	162	0.1837	24.46	74	0.18808	23.09	26	0.19286	22.14
50	173	0.1901	25.13	55	0.18972	23.59	10	0.19112	22.43
80	128	0.2046	26.79	22	0.1921	23.99	3	0.19	22.35
100	102	0.2117	27.65	13	0.196	24.39	0	0.18996	23.10
200	51	0.2374	31.09	1	0.2017	26.64	0	0.18218	23.72
300	38	0.2537	33.48	0	0.20714	27.58	0	0.18	24.35
500	8	0.2772	37.06	0	0.2123	30.24	0	0.1739	25.95
700	2	0.2933	39.63	0	0.22	31.60	0	0.17	27.17

We also notice that guaranteed convergence requires the degree-heterogeneity to be large (> 45). However, at small heterogeneity level the clustering of the BA model is low. In other words, the topology of the BA model does not facilitate the emergence of a single coalition if the degree-heterogeneity is small.

Extended BA Model

We use the extended BA model to investigate the effect of high clustering and large degree-heterogeneity over the emergence of a single coalition. We gradually increase the value of p from 0.2 (low-clustering) to 1.0 (high-clustering) and for each value of the p we increase the initial attractiveness parameter A from 0 to 700. Figure 1 shows that when the clustering of the model is low

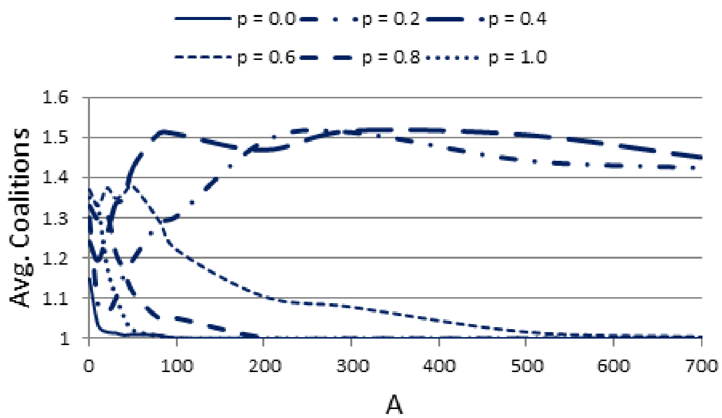

Fig. 1. BA & Extended BA Model: Average no. of coalitions for various values of the initial attractiveness parameter (A) and the clustering probability p

($p < 0.5$), increased degree-heterogeneity does not improve the quality of the emergence. However, we observe **an interesting emergent property** of the networked MAS that when the value of p exceeds 0.5, the likelihood for the convergence into a single coalition is significantly enhanced. Table 2 shows that, unlike the BA model, a single coalition emerges at high clustering ($p = 1.0$) with small heterogeneity (≤ 23). Therefore, our coalition emergence approach, when augmened by the agents through setting a large value for their initial attractiveness parameter and having $p > 0.5$, is also effective in the highly clustered SF networks maintained at small heterogeneity level.

Discussion: The agents in a MAS choose their interaction partners according to the preferential attachment rule of the BA model. In the extended BA model, a fraction of the nodes (depending on the clustering probability p) forms the links according to this rule. However, to guarantee the fast and stable convergence of the proposed coalition emergence approach, agents need to form a network that has fewer weakly connected high-degree hub nodes. A SF network consisting of larger number of hub nodes with strong connections among them converges into sustainable multiple coalitions because of the large accumulated coupling strength of the boundary nodes (which is due to the large coupling srength of the hub nodes). This enhances the competition among the coalitions (the boundary nodes) to attract new agents and may not lead all the agents to converge into a single coalition. Both in the BA and the extended BA model, older vertices not only acquire the largest connectivity but also become naturally interconnected with each other. As a consequence, none of the networks with small value of the initial attractiveness parameter ($A \leq 50$) experience guranteed convergence into a single coalition. By increasing A, agents create a network with fewer hubs and hence the likelihood of the convergence increases. Figure 2 shows the degree distribution of the SF network for four different values of p between $0.0 \sim 1.0$

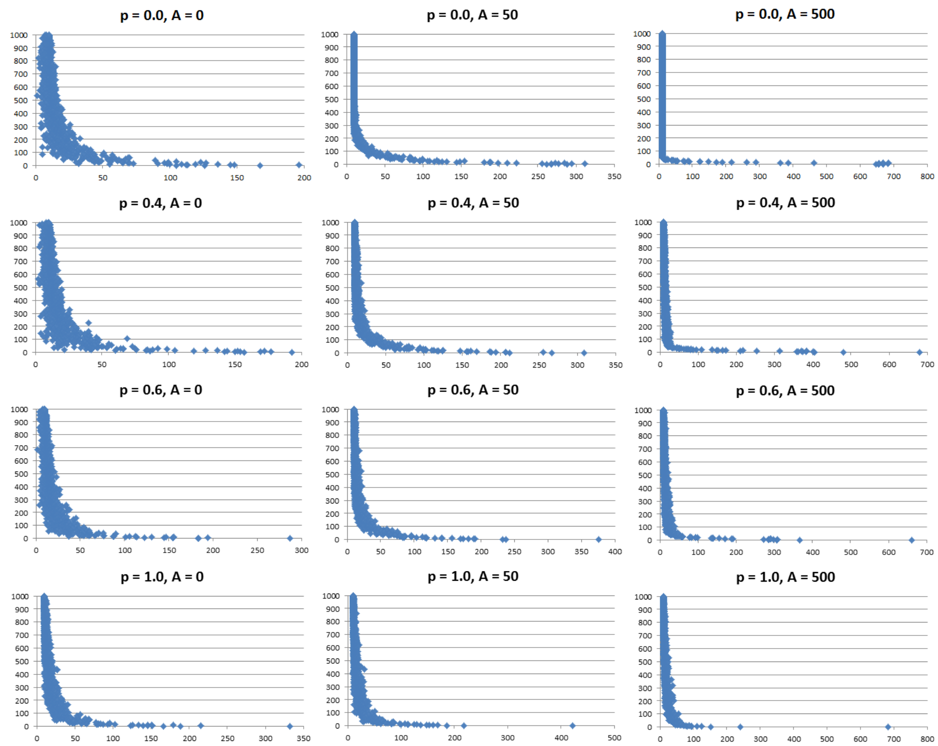

Fig. 2. Degree-Distribution for various values of p and A (x-axis: node-degree & y-axis: node id from 0 to 999)

where for each value of p the initial attractiveness parameter is varied between $0 \sim 500$. In this figure we see that with the increase in the value of p, the number of hub nodes gets decreased. As a consequence, in the BA model (where $p = 0.0$), when the value of A is increased from 0 to 50, the instances of the emergence of sustainable multiple coalitions decreases sharply from 63 to 5 (see Table 2). This occurs because of the decreased number of hub nodes (which is a consequence of the increased degree-heterogeneity).

However, in the extended BA model increased heterogeneity does not enhance the likelihood of the emergence of a sustained single coalition when the clustering of the network is low. For the networks with $p \leq 0.5$ we increased the value of A to as large as 20,000 (the result is not reported here), but did not observe improvement over the single coalition emergence phenomenon. On the other hand, for highly clustered networks (where $p = 0.1$), increase in A significantly enhances the convergence into a single coalition as shown by the sharp slope in Figure 1. This is due to the fact that the number of hubs in the extended model is smaller than the BA model. Figure 2 shows that for any given value of A, the number of hubs are fewer when $p = 1.0$. Therefore, the chances for the emergence of a single coalition is increased when the network is higly clustered as demonstrated by the results.

5 Conclusions and Future Work

In this paper, we present a decentralized coalition emergence approach for the self-interested agents in a MAS operating on large SF networks. Agent interactions with their immediate neighbors are captured by an iterated PD game and we enable the agents to exploit the complex network dynamics to facilitate the convergence into a single coalition. We show that the coalition emergence process is enhanced when the topological insights are embedded into the agent partner selection strategy. We analyzed some of the recent works on this emergence phenomenon among networked agents [15, 1]. Our main observations are: (a) leader based coalition formation scheme incurs overhead cost to maintain network wide communication, (b) fixed configuration and static complex network topology does not represent the real-world characteristics (e.g., growth, variation of topological features etc.) and (c) it is important to incorporate the network dynamics into the dynamics of agent interactions for the emergence of a collective phenomena. Our coalition emergence approach requires the agents to use the node coupling strength and payoff of their single-hop neighbors and do not need a leader to facilitate the coalition formation. Instead of assuming a given pre-established network platform, our agents dynamically choose their interaction partners to form the network. Using a computational model we have performed extensive simulations and have shown that both increased degree-heterogeneity and clustering facilitates the emergence of a sustained single coalition over various types of SF networks.

As future work, we plan to verify our simulation results analytically. We also plan to extend our model for incomplete information games where agents do not know their neighbors payoff.

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