Game-Theoretic Coalition Formation Using Genetic Algorithm and Agent-Based Modeling

Gayane Grigoryan, Andrew J. Collins, Wimarsha Jayanetti, Dean Chatfield

Old Dominion University, Norfolk, Virginia, United States

Abstract. Understanding the behavior of coalition formation is of significant importance. This paper investigates coalition formation in agent-based modeling using a genetic algorithm. Agent-based simulations are utilized to gather data on coalition formation by employing an inverse generative approach. The study encompasses a wide range of game sizes and examines various characteristics of coalition formation. Specifically, it analyzes the average number of coalition suggestions per game size and the time required to achieve the final coalition structure based on respective fitness functions. By delving into these aspects, this research contributes to a deeper understanding of coalition formation dynamics in agent-based simulation models.

Keywords: Modeling and simulation · Agent-based modeling · Cooperative game theory · Machine learning · Genetic algorithm.

1 Introduction

Understanding coalition formation is crucial for enhancing our understanding of social and behavioral dynamics. Coalition formation helps to better understand the emergence of power structures and collective decision-making processes within human societies and organizations [1]. Additionally, the study of coalition formation informs strategies for conflict resolution and cooperation by identifying factors that drive the formation of alliances and comprehending the dynamics of conflicts [21]. Also, investigating coalition formation sheds light on social influence and the diffusion of ideas, offering valuable insights into opinion formation, the emergence of social norms, and the spread of information through social networks [9]. This knowledge is instrumental in designing effective communication campaigns and addressing societal issues.

Various techniques have been employed to gain deeper insights into coalition formation tendencies and structures [23], and further investigation is needed to expand our understanding in this area [19]. In particular, the size of the game has not been sufficiently explored, and to the best of our knowledge, this is the initial endeavor to investigate the patterns and the connection between game sizes and the formation of the final coalition structure within the realm of agent-based modeling. As part of our investigation, our focus has been on comprehending the relationship between game size and the dynamics of coalition formation. We have explored the average number of suggestions and time to reach the final coalition structures considering different game sizes.

In this paper, we investigate these questions by coalition formation scenarios (referred to as "games") with varying numbers of players/agents and their resultant solutions. To generate the required data, we employ the Inverse Generative Social Science (IGSS) approach, which combines a genetic algorithm and agent-based modeling. Coalition formations are defined using a hedonic game, a form of cooperative game theory, model. This approach enables us to simulate realistic agent behaviors by leveraging observed social phenomena. The analysis presented in this paper extends those given in our previous conference paper [7]. The next section describes the background of this research. Section 3 outlines the methodology, Section 4 presents the results, and Section 5 concludes the work.

2 Background

This section provides an overview of studying the impact of coalition sizes on coalition formation, specifically using Genetic Algorithms (GAs) in Agent-Based Modeling and Simulation (ABMS). It also briefly covers cooperative game theory and the foundational agent-based simulation used in the computational experiment.

First, we recognize the significance of studying the impact of game sizes on coalition formation. Comparing various game sizes within the context of coalition formation holds importance for several compelling reasons. Firstly, it allows us to understand how the size of a game influences the dynamics of coalition formation. By examining games with varying numbers of players/agents, we can identify patterns, trends, and challenges that emerge as the complexity of the game increases. Secondly, comparing different game sizes helps us assess the scalability and generalizability of coalition formation strategies. A strategy that works well in small-scale games may not necessarily be effective or feasible in larger-scale games. This information is valuable for decision-makers who need to apply coalition formation techniques in diverse contexts, ranging from small groups to large organizations or societies. Lastly, comparing different game sizes provides insights into the trade-offs and challenges associated with coalition formation in complex systems. Larger games typically involve more players and more intricate interactions, which can lead to increased complexity and coordination difficulties. By exploring how coalition formation dynamics change as game sizes vary, we can uncover key factors that influence successful coalition formation and identify strategies that are effective across different scales.

Now, we delve into the essential components employed in conducting the experimental analysis.

2.1 Inverse Generative Social Science (IGSS)

Inverse Generative Social Science (IGSS) is a methodology introduced by Vu et al.[26] in 2019, aiming to determine agents' behaviors in an agent-based simulation by matching the simulation outputs with provided real-world datasets. IGSS employs machine learning techniques to generate mathematical representations of behaviors within sub-models, with genetic programming being a popular approach for implementing IGSS [17, 13]. This approach not only provides theoretical interpretability but also enhances our understanding of human behavior [26, 10], and contributes to model explainability, an essential aspect of modeling complex problems [14, 11, 20].

2.2 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are computational methods inspired by natural selection, pioneered by John Holland, a key contributor to Agent-Based Modeling and Simulation (ABMS) [18]. GAs employ stochastic processes to select and mutate a population of potential solutions represented as chromosomes, composed of ordered genes that influence behavior and determine fitness. GAs iterate through generations, repeatedly evaluating and evolving chromosomes to find the most optimal solution. While GAs have been applied in ABMS for parameter exploration, their application in the context of Inverse Generative Social Science (IGSS) is relatively limited.

2.3 Cooperative Game Theory

Cooperative game theory is a branch of game theory that focuses on the formation of coalitions among agents [4, 15]. It aims to understand how agents form groups and allocate their resources within these coalitions. The form of cooperative game theory considered is called hedonic games [3, 15]. Hedonic games are games where each player (agent) has a preference relation over all the possible coalitions in which they are a member [5].

Similar to non-cooperative game theory, there are a variety of different solution concepts connected with cooperative game theory [24, 4]. In the research presented in the paper, only the core is considered (strictly, it is the core partition for hedonic games [3]). The core partition a stability criteria of a partition such that no subset of players has an incentive to for a new coalition. For a given game, the core is not guaranteed to exist; however, in this research, we only consider games where the core does exist.

Other solution concepts for cooperative game theory (and hedonic games in particular) for example, Shapley Value, nucleolus, and the Kernel exist [24, 4]. Though we do not explicitly consider these other solution concepts some are accounted for in our research. For example, the nucleolus is always part of the core (if it exist) and the kernel; as we are only considering games with a non-empty core, we are also considering the nucleolus and part of the kernel.

Since a player on their own can be considered in a coalition (known as singleton coalition) and we only allow players to be a member of a single coalition at any given time, our games always present a covering disjoint collection of coalitions; this is known as a coalition structure and is an important aspect of hedonic games.

2.4 Agent-based simulation of strategic group formation

The agent-based modeling approach refers to a computational modeling technique that simulates the behavior and interactions of individual agents within a given system [12]. This approach allows us to study the emergence of complex phenomena and understand the collective behavior that arises from the interactions of autonomous agents. In our study, an agent-based simulation of a strategic coalition formation scenario has been developed, building upon prior research [6, 25], and its validity has been confirmed through comparisons with results from human experiments [16].

3 Methodology

The methodology starts with developing the base simulation framework, as outlined in [8, 5]. This simulation serves as the foundation for conducting the computational experiments and analyzing the results. The base simulation describes a hybrid agent-based model using cooperative game theory. Next, the Inverse Generative Social Science (IGSS) approach way applied to perform computational experiments and generate the necessary data. The effectiveness of this approach has been validated in our previous research discussed in [7]. The overview of the steps employed to conduct the experiments and generate the data is presented in Table 1.

Table 1. Process of coalition formation analysis

	Overview of coalition formation analysis
1	Define the list of games to be considered;
2	Specify the fitness criteria for evaluating the coalition formations;
3	Utilize a genetic algorithm to conduct simulation runs for multiple games;
4	Perform a batch run for simulation run, for each game;
5	Record the average number of coalition suggestions from each batch run and game;
6	Analyze the average coalition formation suggestions required;
	Evaluate the quality of the analysis based on the fitness criteria;
	Identify patterns, and trends, that contribute to successful coalition formations.

This process outlines the steps involved, starting from defining the game list and fitness criteria, followed by executing a genetic algorithm, which is evaluated using the output of multiple games, each with its own batch runs. The experiment was run for two different fitness criteria. The first fitness criteria is the number of coalition suggest required before the a core partition is found within a given game with fewer suggestions being better. The second is the computational time required to find a core partition. In both case, an extreme upper limit of 100,000 suggestions was use in case the core partition was not found.

We use a chromosome that represents the sequence of behaviors agents undertake in each simulation round, particularly focusing on the coalition suggestions made by an agent to others. Our genetic representation approach uses variable length chromosomes (VLC) and non-binary genes [2]. The VLC feature allows for the chromosome length to mutate. Genes serve as representations of behaviors, specifically coalition suggestion types made by agents. A coalition suggestion occurs when a new coalition is proposed to a group of agents. If all the agents involved perceive the suggested coalition as beneficial, in terms of increasing their utility, the coalition will form. Each gene within the chromosome corresponds to a specific type of suggestion.

The coalition suggestions were randomly generated based on suggestion type. Due to the stochastic nature of the simulations, a single run is insufficient to accurately determine the coalition structure. Therefore, we need to conduct multiple runs (iterations) to evaluate the outcomes more effectively. This is where the batch run comes into play. A batch run refers to the execution of multiple simulation runs in a sequential manner in order to obtain reliable results. This is repeated for multiple games so the results are not biased by one game. In our genetic algorithm (GA), we use a fixed population size of 100 individuals, employing tournament selection, and setting the crossover rate at 80% and the mutation rate at 3% as established standards in the GA community [22]. Our analysis covers game sizes from three to nine agents, running the GA for 7,000 generations per game size, resulting in a total of 63 million simulation runs. The simulation is implemented in JAVA, while the game generator is implemented using C++.

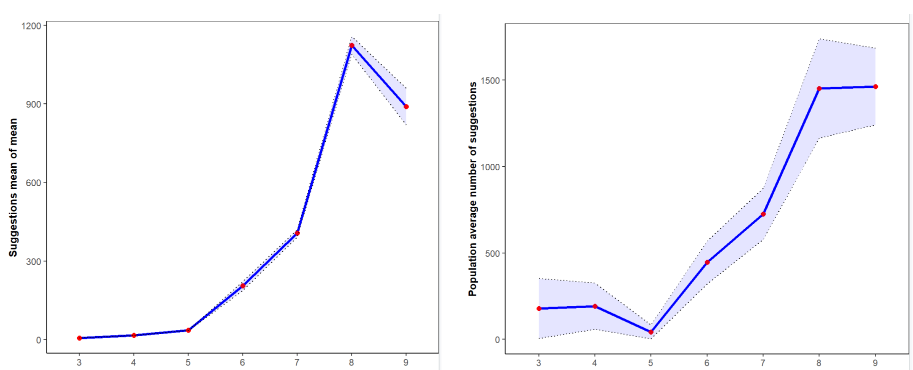
During each simulation run, our objective is to discover a solution, to the game; this solution is in the form of a coalition structure, thereby exploring various coalition formation scenarios and generating a range of potential coalition structures. In order to assess the effectiveness of each batch run, we require a metric for evaluation. One possible metric is the mean number of suggestions, which we call "suggestion mean", and this measure indicates the average quantity of suggestions made during a simulation run; which is averaged over the batch runs. Once we have assessed the suggestion means for each batch run, we proceed to evaluate these runs across different games. We calculate the average number of suggestion means for the games, considering the data collected from the batch runs. This allows us to determine the mean number of suggestions for each specific game, providing insights into the suggestion patterns and performance across various gaming scenarios. This metric is referred to as the "suggestion mean of the mean."

$$SMM = \frac{\sum_{Game=1}^{g} \frac{\sum_{BatchRun=1}^{m} CSC}{m}}{g} \tag{1}$$

Where, SMM is the suggestion mean of mean, and CSC refers to the coalition suggestion count for a given simulation run. In total, 30 different games are generated to test each chromosome (each game had a non-empty core). These different games are translated into their own simulation. To account for stochastic variability, each simulation is run 30 times. The average number of suggestions made across these 900 simulation runs is calculated, representing the "suggestion mean of mean." This metric provides insights into the average suggestion behavior for a specific game type. The goal of the analysis is to extract insights and observations from the collected data and findings.

4 Results

In this section, we present the outcomes of our analysis. Figure 1-a shows as the game size increases, the suggestions mean of mean tends to increase, indicating that larger games require more coalition suggestions among agents to reach a solution. However, an interesting exception is observed at a game size of nine, where there is a decrease in the suggestions mean of mean. This suggests that there might be certain complexities or dynamics present in larger games that affect the agents' behavior. Moreover, the rate of increment in the suggestions mean of mean differs across different game size ranges. Specifically, for game sizes ranging from 3 to 5, the rate of increase is relatively slower compared to the range of 5 to 8. The blue ribbon in the figure represents the confidence interval (CI) for the mean estimate of the suggestions. The interval is calculated based on the mean estimate and its standard deviation, indicating the range within which the true population mean is estimated to lie with a 95 % confidence level. In Figure 1-a, the CI is narrow for game sizes 3 to 8, indicating a more precise estimate with less variability. However, for game size 9, the CI widens, suggesting increased uncertainty in the estimate. This disparity implies that the impact of game size on the agents' coalition suggestions may vary depending on the specific range or imply exponential growth in SMM with stochastic error variability; further research is required to determine which is the case.



(a) Fittest chromosome' suggestion mean of mean

(b) Population average of suggestion mean of means

Fig. 1. Comparing variation in suggestion means across different game sizes

In analyzing the results, we initially anticipated an increasing trend in the average number of suggestions in the population as the game size increased (1-b). This expectation was based on the intuition that larger game sizes would introduce more possibilities to consider, hence requiring a greater number of suggestions to reach a solution. However, contrary to our initial expectations, the graph did not exhibit a consistent upward trend. The observed deviations from our expected trend can be attributed to certain quirks or factors that were taken into consideration during the analysis. These quirks might include complex dynamics within larger game sizes; specifically, the influence of specific game scenarios. Therefore, the unexpected graph pattern can be attributed to quirks, indicating that the relationship between game size and the number of suggestions is more intricate than initially assumed. Additionally, the CI exhibits a more compact range around Game 5 in comparison to the other games, indicating a higher degree of precision and reduced variability in the estimate.

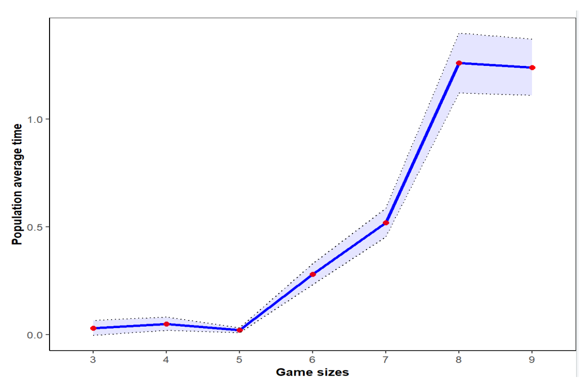
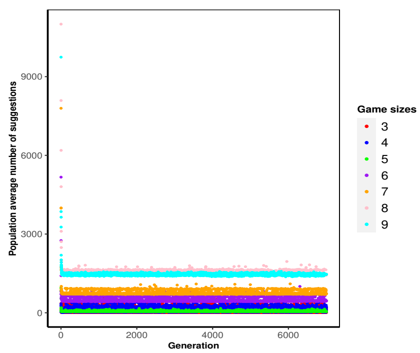
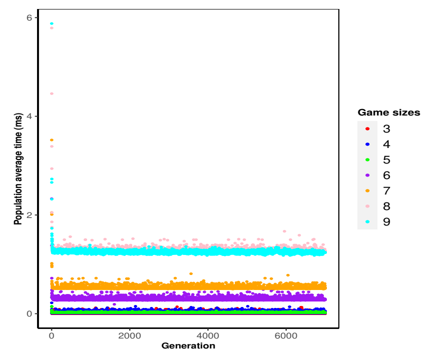


Fig. 2. Coalition formation time across different game sizes

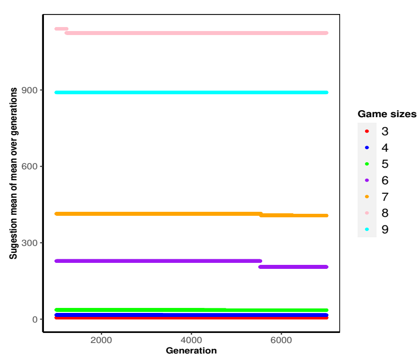
Next, we conducted a comparison of the average time required for coalition formation across different game sizes (Figure 2). Interestingly, we observed that Game 5 exhibited a shorter time to reach the solution compared to games with 3 or 4 agents. Furthermore, Game 9 displayed a slightly shorter time for coalition formation compared to the game with 8 players. Moreover, when examining the CI, a subtle distinction emerges between Game 8 and Game 9, with the CI for Game 8 displaying a slightly wider span, indicating a slight increase in uncertainty for the estimated value. These findings suggest that factors beyond game size, such as constraints and complexities, significantly influence coalition formation. Constraints like limited resources and conflicting objectives among agents can impact formation time. Conflicting player requirements may require more negotiations and iterations. Game dynamics complexities, such as interdependencies and diverse preferences, introduce decision-making challenges affecting the time to establish a stable coalition structure.



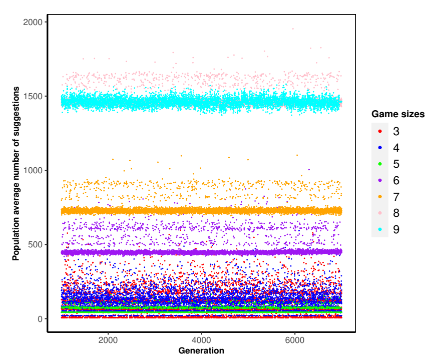
(a) Population average number of suggestions across generations



(b) Population average time across generations



(c) Population suggested mean of mean: truncated



(d) Population average number of suggestions: truncated

Fig. 3. Analysis of coalition suggestions across generations

The analysis of suggestion outcomes across generations, based on the genetic algorithm, reveals a consistent trend in coalition suggestions per generation, showing subtle improved performance as the generations progress. As anticipated, larger game sizes generally require a greater number of suggestions. Games with eight players exhibit a higher mean number of suggestions compared to games with nine players. Figure 3-a demonstrates that, initially, game size eight takes more than 9000 suggestions to reach the core coalition. Similarly, figure 3-b shows that, at the beginning of the generation, game size three also takes longer to find the coalition structure. Figures 3-c and figure 3-d present truncated versions of coalition suggestions across different generations. Both graphs consistently indicate that game size eight consistently outperforms game size nine in terms of the number of observed coalition suggestions and the time taken to form the final coalition structure. Notably, the game with five players demonstrates comparable or closely aligned suggestion counts to games with 3 and 4 players across generations in attaining the final coalition structure.

This analysis highlights that the size of the coalition is not the sole determinant in the formation of the final coalition structure. Factors such as limited number of games, game complexity and other constraints play a significant role in shaping the coalition formation process. These findings emphasize the importance of considering multiple factors in coalition formation research.

5 Conclusions

This paper presents an analysis of the coalition formation problem, examining the influence of game sizes on the trends of coalition formation. The study utilizes inverse generative social sciences; specifically, genetic algorithm-based approach; and agent-based modeling and simulation (ABMS) approaches. The computational experiment conducted reveals that, besides game sizes, other factors could significantly impact the time and performance of coalition formation, as indicated by the coalition suggestions and time. The results also indicate the presence of learning in the genetic algorithm; however, it is suggested that increasing the number of generations would yield clearer insights. Hence, additional extensive computational experiments are required to obtain definitive findings from this approach. The significance of these findings is that incorporating coalition formation into ABMS might require a deeper understanding of the dynamics than initially anticipated.

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