Application of Game Theory and Evolutionary Algorithms in Solving Conflicts in Social Systems

Shpend Ismaili[1], **Stefka Fidanova**[2*]

[1] *University of Tetovo*
Tetovo, Macedonia
E-mail: shpend.ismaili@unite.edu.mk

[2] *Institute of Information and Communication Technologies*
Bulgarian Academy of Sciences
Sofia, Bulgaria
E-mail: stefka@parallel.bas.bg

[*] *Corresponding author*

Received: October 23, 2017 **Accepted: December 20, 2018**

Published: September 30, 2019

Abstract: *Modeling of behavior of social system is of high importance. It is very complex and is difficult to predict the conflicts which can arise between the different agents in the system. The behavior of an individual is changed during the time according the behavior of other individuals. There is interaction between individuals themselves and individuals and environment and all they need to be taken in to account. The social system can be represented as a multi-agent system with various types of participants. In this paper we model conflict situations during a protest applying game theory and evolutionary algorithm.*

Keywords: *Multi-agent system, Game theory, Evolutionary algorithm.*

Introduction

Social systems are very complex and unpredictable. They are composed of a set of individuals acting in the environment and interacting (co-operating) among themselves, evolving in an autonomous manner and motivated by their beliefs and goals as well as from the conditions of their social environment. These social systems are truly complex adaptive systems, they have the ability to learn and change the behavior of an entity that represented the man here, optimizing some properties over time [17]. This evolution of individuals in comparison with other individuals and the environment can be presented as a result of competition between the representatives of the population of resources, that is, how the interaction between individuals or individuals and the environment is able to adapt their behaviors [15].

Conflicts in society are due to two main reasons: misunderstanding and different interests. In the first, it can happen because not every individual (agent) own the same information. So everyone can make different conclusions based on different assumptions. In the second, the information is complete in both individuals (agents). However, the conflict comes as a consequence that individuals themselves have different desires, beliefs, or goals [15].

Modeling of these systems will be accomplished with the help of Agent Based Modeling (ABM) composed of sets of software entities (agents) interacting with each other and with their environment [21]. These agents are autonomous, reactive, proactive and sociable. Which means they can decide on their own and then act. They can react on the basis of their perceptions (information) that they take from the environment where they operate. They can influence the environment by interpreting the environment in order to adapt it so that they can achieve their goals. They can socialize, or to share resources with other agents in order to achieve their goals more easily and quickly. In this sense, the agent's paradigm represents very well the individuals in the social systems. ABM can be realized with several agents, which can be of different types located in an environment where the behavior of agents is monitored. Observation of agents can help in the analysis of collective behavior and the evolution of systems. This provides a platform for empirical study of social systems. In the model presented, protests of dissatisfied civilians on the central government are modeled, where some elements are invented [7]. The game theory and evolutionary algorithm are applied.

The game theory [22] is widely used in the modeling approach [8], based on agents [3] to model a human as unity. The interactions between real agents will be presented with the game theory, for example, the "prisoner dilemma". This game is composed of players, player strategies, that is, the choice made by players and the payoff matrix. These strategies evolve on the basis of the opponent's choice and, to be more realistic, this game will be used by the "iterated prisoner dilemma" IPD [2], which implies that players revise their strategies on the choice that the opponent makes. With IPD we can find out how the players increase their profits depending on the change in situation [18].

The choice or strategies of players evolve, therefore this evolution will be presented with evolutionary algorithms (EA) [10, 16] specifically with co-evolutionary algorithms (CEA). CEA [24] are heuristic techniques that can be used to find approximate solutions in the general optimization problems.

Combination between evolutionary algorithms, game theory and multi-agent systems is used to analyze evolutionary dynamics of multi-agent systems. These learning algorithms are apply to study complex strategic interactions like parameter tuning of complex systems, trading in stock markets and avoidance of collisions in multi-robot systems [5]. Other application is for solving optimization problems in many different areas with varying features and characteristics [4]. Every application is specific, taking in to account the particular peculiarities of the problem.

In our previous works on the same problem we describe the different types of agents and their interaction with Generalized nets [11] and we estimate the agent behavior using intuitionistic fuzzy sets [12]. Our contribution in this work is application of co-evolutionary game theory on multi-agent system for modeling conflicts in social system during a protest. A co-evolutionary method is expressed with CEA, which is based on the strategies of competitors agents continually evolving [1].

Problem formulation

A conflict is a serious disagreement between two persons, when strive to achieve their goals. In this paper we try to understand variations of human behavior according the situation. We try to simulate collective behavior, representing different groups in a conflict. We focus on development of combination between multi-agent system, CEA and game theory, to learn the behavior caused by the interaction between the agents. Some computer models in concrete protests exist in a literature: model of trade protest [13], model of the violence in London [6], model of revolution [14], etc. These are specific situations, so the models are not applicable in other type of violence.

The structure of our model of civil violence consists of individuals, environment and empirical rules. Our software agents model polis officers and civilians. Accurate modeling is crucial for more realistic representation of possible situations. Peaceful civilians are neutral participants, who could react to external or internal stimulus. Police officers retain the order by the insertion of the active civilians in jail and through strategies that choose depends on the success of the management and control of violence. The police officers perform two tasks in a direct way: arrest active protesters and move in space. They are representative and a protectors of the government.

Civilians are much more complex individuals, than the police officers. They communicate between each other. They decides whether to be active or not. The civilian agents can change from active to peaceful and from peaceful to active. The functioning of the system depends of the empirical rules. Empirical rules guide the interactions of agents and ensure the functioning of the system.

Game theory

The game theory, or the theory of strategic interaction, analyzes situations in which the condition of the agents depends directly on the choice of other agents. Each agent must anticipate the choice or decisions of other agents in the game, when making a decision. The game theory is not able to solve all the problems, because it works only when people play rationally. If players play to maximize the profits from them, then their behavior is considered rational. In game theory, the goal is to observe the decisions that players take when they do not interact with each other, but only play together in the game [8].

Prisoner dilemma

The prisoner dilemma is one of the most familiar games in this area and the most used example [2, 3]. Two people have been arrested for committing a crime. The police officers have not enough evidence to convict the suspects and therefore decide to testify against each other. Police officers inform each of them that if he testifies against his friend, he will be released, provided that his friend has not testified against him. The aim of each suspect is to minimize potential years of imprisonment. The two suspects decide to testify. It would have been better for both of them if none of them testified, because the police officers did not really have enough evidence to convict them.

Definition of game

To define a game, we need:

- Players;
- Strategies for each player;
- Player's profit. The profit for each player depends on other players' strategies.

Let us get back to the example of the prisoner's dilemma. There are two players in the game, the first suspect and the second suspect. Both must decide simultaneously in separate rooms whether they will testify or not against each other. So each player has two strategies: to testify or not to testify. Typically, all the necessary information is recorded in the form of a matrix, called a matrix of profits. The rows of this matrix represent the strategies of the first player; columns represent the strategies of the second player. The numbers in the cells represent the profit of the respective players [20].

Co-evolutionary algorithm

A co-evolutionary algorithm is an evolutionary algorithm that, in order to assess fitness (goodness), uses internal subjective measurement [19]. So, instead of evolving a spatially distributed population of similar individuals, representing a global solution, it is more appropriate to co-evolve subpopulations of individuals representing specific parts of the global solution. The co-evolutionary algorithm is appropriate to model interactions in the theory of gaming between groups because they have different strategies depending on the strategies of their opponents. The use of this method maximizes the behavior of each entity that resonates in a rational way to maximize its gains. Thus, a player sees the honorable strategies and adapts them to the dynamics of the medium, which improves the time of the opposing strategy. The CEA offers analysis of one scenarios with repeated interactions in modeled social systems. Table 1 represents the analogy between the parameters of co-evolutionary algorithms and the parameters of game theory.

Table 1. Analogy between the parameters in game theory and CEA

CEAs	**Game theory**
Fitness	Payoff
Individuals/Chromosomes	Strategy
Selection of fit individuals	Selection of good strategies
Selection	Learning by replication
Crossover	Learning by social exchanges
Mutation	Learning by experimenting

Co-evolutionary algorithm and game theory for modeling conflict situations

In this paper we consider the modeling of conflict situations during a protest, which is a consequence of the dissatisfaction of the population with the central government. The model is based on the concept of the evolutionary theory of the game [23], co-evolution algorithms and is built according to existing models of Epstein [7] and Yui et al. [25] with certain modifications. Epstein model decentralized rebellion against a central authority and communal violence between two ethnic groups. This model is able to present violence dynamic via simple empirical rules and equations. Yui et al. [25] extended Epstein's model [23] by introducing specific movement strategies in order to correct random movement of the agents. In both models there are two types of agents.

In this paper, three types of agents are distinguished: agents who represent guardians of the central government, that is police officers; active and peaceful civilians who in some cases can express their dissatisfaction with the central government or if they have interest from the central government will remain calm. These agents are placed in a 2D grid and can have 8 visions of movements, based on Moore neighborhood [9].

Bearing in mind, that the game theory is composed of players, their strategies, and the matrix of profit, then in the case that we consider players will be concrete groups that play a strategy and have a certain matrix of profits that changes from the actual situation of the agents in 2D space.

This is a set of three matrices that corresponds to the scenes when: the number of officers is less, greater or equal to a number of active civilians and are further represented in Tables 2-4. Each player has the opportunity to cooperate (C) or not to cooperate (D). This notation is different for different types of agents.

Active civilians will have value:

- C (cooperates) if the active agent is not an aggressive, for example, not violence, does not involve police officers or does not urge peaceful civilians to join the crowd;
- D (does not cooperate) for other cases.

Police officers will have value:

- C (cooperates) when only defending civilians or state institutions, does not attack;
- D (does not cooperate) when he actively monitors protesters to arrest them.

These values of agents that are taken and adapted for our model are from [25]. Each group of agents has opposite goals. Active civilians aim to create significant violence to win the support of peaceful civilians and to provoke large-scale riots, but to avoid arrests. Police officers aim to suppress the conflict and preserve civil order within the regime, serving as defenders of society and government by minimizing losses. It is also taken into account that the police officers are loyal to the government.

With use of evolutionary strategies of co-evolutionary algorithms based on the Table 1, which presents the parallel of game theory and evolutionary algorithms, we can monitor the situation, which can be evolved by a number of counter-agents. Thus, it can be observed when the strategies of the respective agents are based on the punishment (P), temptation (T), reward (R) or sucker's payoff (S).

Each agent is represented by 14-bit binary string. The first bit is 1 if agent is police officer and 0 if he is civilian. The second bit is 1 if the agent is C and 0 if he is D. Next 4 bits corresponds to the 4 possibilities when the number of police officers is less than the number of active civilians, after 4 bits corresponds to the 4 possibilities when the number of police officers is greater than the number of active civilians and the last 4 bits corresponds to the possibilities when the number of police officers is similar to the number of active civilians. Every one of the bit from this groups of 4 bits is 1 if the situation can happen and 0 if it cannot happen.

In the co-evolutionary algorithms the fitness function of each member of the first population is dependent on the structure of the other populations (in our case active and peaceful agents and the police officers). The cumulative fitness of an individual of the first population is calculated by the formula:

$$f_i = \sum_{j=1}^{N} G(i,j), \tag{1}$$

where j is a member of the other populations, N is the number of the members of the other populations and G is a function which shows the relation between the members of different populations.

Matrices of profits are based on the objective (Eq. (1)) of each group of agents to increase their profits and reduce losses in different situations. We are considering a scenario based on the above definition of matrix values, when police officers are less than active civilians. In a given spatial interaction field we will have the following justification (Table 2):

- If the two groups are D, active civilians are the winner because of their larger number. Gains will be for agents, police officers will have S, while active civilians will be rewarded with T.
- If the two groups are C, the profits will be in favor of the police officers, as these active civilians will have missed the case to take advantage of their quantitative advantage over the police officers. The profits will be: for the active civilians we will have S, whereas for the police officer who avoid contacts as they are less than the reference number specified above, there will be T.
- If the police officers are C and the active civilians are D, we will have logical equality because the police officers are not attacking because of their unequal number and the active civilians attack or communicate with the peaceful civilians by using their number advantage. The equalized profit for both groups will be R.
- If the police officers are D and the active civilians are C then there will be punishment for both groups as they do not act to justify their number in the space they have to act on. The profits for the two groups will be P.

Table 2. Matrix of profits, when the number of the police officers is less than active civilians

	Active civilians cooperate	**Active civilians do not cooperate**
Police officers cooperate	T:5, S:1	R:4, R:4
Police officers do not cooperate	P:3, P:3	S:1, T:5

We consider a scenario in which the number of police officers is greater than active civilians, and we will have the following justification (Table 3):

- If the two groups are D, the police officers will win the top because of their numerical superiority. Their successful intervention to control tensions will be rewarded with the T award. Active civilians, given the big sacrifices caused by their small number in space, will be rewarded with S.
- If the two groups are C, the profits, they will recover in favor of the active civilians because the police officers have lost the opportunity to arrest protecting the population. For C active civilians, it was valuable because they successfully escaped conflicts with more police officers. The profit of the active civilians will be T, while the police officers will be P.
- If the police officers are C and the active civilians are D, both groups receive a gain P, and C and D are used inappropriately. Police officers must have D to deal with active civilians. Active civilians must have C to avoid the open clash in applying the dominant law and the victims.
- If the police officers are D and the active civilians are C, then a logical equality is achieved, where the multiple dominates the minority, avoiding direct conflict and arrest.

This is the best situation as the winnings of the two groups are leveled and receive a reward R.

Table 3. Matrix of profits, when the number of the police officers is greater than active civiliens

	Active civilians cooperate	**Active civilians do not cooperate**
Police officers cooperate	P:1, T:5	P:3, P:3
Police officers do not cooperate	R:4, R:4	T:5, S:1

We consider the scenario based on the above definition of earnings matrix values, where the number of police officers is equal to the active civilians, and we will have the following justification in a given spatial interaction field (Table 4):

- If the two groups are C then we have a logical equality, where everyone has their own position and no one has numerical superiority. Both groups will therefore receive R.
- If both groups are D, the police officers can not be sure of their victory, as well as the active civilians, and if they are attacking, it is unclear whether they will be able to avoid arrest. The win for both groups will be P.
- If the officers are C and the active civilians are D, then the active civilians they are attacking will not be arrested by the police officers and will therefore have T profit, while the police officers wanting only to keep their own position will lose and gain P .
- If the police officers are D and the active civilians are C, then the police officers attack and use the case that the active civilians are not violence, do not attack and do not communicate with peaceful civilians. Profits for police officers will be T, while for the active civilians will be P.

Table 4. Matrix of profits, when the number of the police officers and active civilians are equal

	Active civilians cooperate	**Active civilians do not cooperate**
Police officers cooperate	R:4, R:4	P:0, T:6
Police officers do not cooperate	T:6, P:0	P:1, P:1

Conclusion

In this paper a conflict between representatives of government (police officers) and civilians (active and peaceful), during a protest, is represented with the help of game theory and co-evolutionary algorithms. With this game model a variety of situations can be played. It can be used to train the police officers simulating different situations. Other application is predicting possible conflicts and better estimation of the setup and optimizing the number of needed police officers as well as optimizing police officers responses to minimize critical situations protecting civilians.

Acknowledgements

Work presented here is partially supported by the Bulgarian National Scientific Fund under the grants DN 02/10 "New Instruments for Knowledge Discovery from Data, and their Modeling" and DN 12/5 "Efficient Stochastic Methods and Algorithms for Large-Scale Problems".

References

1. Aguirre J., D. Papo, J. M. Buldu (2013). Successful Strategies for Competing Networks, Nature Physics, 9, 230-234.
2. Axelrod R. (1987). The Evolution of Strategies in the Iterated Prisoner's Dilemma, Genetic Algorithm and Simulated Annealing, Lawrence Davis (Ed.), London, Pitman.
3. Axelrod R. (2006). Agent-based Modeling as a Bridge between Disciplines, Handbook of Computational Economics, Vol. 2, Agent-based Computational Economics, Tesfatsion L., K. Judd (Eds.), New York, North-Holland.
4. Byrski A., R. Drezewski, L. Siwik, M. Kisiel-Dorohinscki (2015). Evolutionary Multi-agent Systems, The Knowledge Engineering Review, 30, 171-186.
5. Bloombergen D., K. Tuyls, D. Hennes, M. Kaisers (2015). Evolutionary Dynamics of Multi-agent Learning: A Survey, Artificial Intelligence Research, 53(1), 659-697.
6. Davies T. P., H. M. Fry, A. G. Wilson, S. R. Bishop (2013). A Mathematical Model of the London Riots and Their Policing, Scientific Reports, 3, Article number 1303.
7. Epstein J. M. (2006). Agent-based Computation Models and Generative Social Science, Generative Social Science: Studies in Agent-based Computation Modeling, Epstein J. M. (Ed.), Princeton, New Jersey, Princeton University Press, 4-46.
8. Gibbons M. M. (2001). An Introduction to Game-theoretic Modeling, Student Mathematical Library, American Mathematical Society.
9. Gray L. (2003). A Mathematician Looks at Wolfram's New Kind of Science, Notice of the American Mathematical Society, 50, 200-211.
10. Holland J. (1992). Adaptation in Natural and Artificial Systems, Cambridge, MIT Press.
11. Ismaili S., S. Fidanova (2018). Representation of Civilians and Police Officers by Generalized Nets for Describing Software Agents in the Case of Protest, Studies of Computational Intelligence, 728, 71-78.
12. Ismaili S., S. Fidanova (2019). Application of IFS for Conflict Resolution Modeling and Agent Based Simulation, Int J Bioautomation, 23(2), 175-184.
13. Kim J. W., R. A. Hanneman (2011). A Computational Model of Worker Protest, Journal of Artificial Societies and Social Simulation, 14(3), doi: 10.18564/jasss.1770.
14. Makowsky M. D., J. Rubin (2011). An Agent-based Model of Centralized Institutions, Social Network Technology, and Revolution, Towson University Department of Economics, Working Paper 2011-05.
15. M'hamdi A., M. Nemiche, R. Lopez, F. Ezzahra, K. Sidati, O. Baz (2017). A Generic Agent-based Model of Historical Social Behaviours Change, Advances in Complex Societal, Environmental and Engineering Systems, Nemiche M., M. Essaaidi (Eds.), Springer, 31-49.

16. Michalewicz Z. (1992). Genetic Algorithms + Data Structures = Evolution Programs, Berlin, Springer Verlag.
17. Miller J. (2009). Complex Adaptive Systems: An Introduction to Computational Models of Social Life, Princeton University Press.
18. Nishizaki I., M. Sakawa, H. Katagiri (2004). Influence of Environmental Changes on Cooperative Behavior in the Prisoner's Dilemma Game on an Artificial Social Model, Applied Artificial Intelligence, 18(7), 651-671.
19. Potter M., K. De Jong (2000). Cooperative Coevolution: An Architecture for Evolving Coadapted Subcomponents, Evolutionary Computation, 8(1), 1-29.
20. Quek H. Y., C. K. Goh (2007). Adaptation of Iterated Prisoner's Dilemma Strategies by Evolution and Learning, Proceedings of the IEEE Symposium Series on Computational Intelligence, Computational Intelligence and Games, Honolulu, Hawaii, USA, 40-47.
21. Shalizi C. R. (2016). Methods and Techniques of Complex Systems, Science.
22. Von Neumann J., O. Morgenstern (1955). Theory of Games and Economic Behavior, Princeton University Press.
23. Weibull J. (1992). Evolutionary Game Theory, Cambridge, MA, MIT Press.
24. Weigand P., W. Liles, K. De Jong (2001). An Empirical Analysis of Collaboration Methods in Cooperative Coevolutionary Algorithms, Proceedings of the Genetic and Evolutionary Computation Conference (GECCO), 1235-1242.
25. Yiu S. Y., A. Gill, P. Shi (2002). Investigating Strategies for Managing, Civil Violence Using the MANA Agent Based Distillation, Proceedings of the Land Warfare Conference, Brisbane, Australia, 475-484.

Assist. Prof. Shpend Ismaili, Ph.D.
Email: shpend.ismaili@unite.edu.mk

Shpend Ismaili has received his M.Sc. Degree in Computer Science from FON, Skopie, the first private university of Macedonia. He works as an Assistant Professor in Tetovo University, Macedonia. His main field of research is the application of multi-agent systems for modeling social processes.

Prof. Stefka Fidanova, Ph.D.
Email: stefka@parallel.bas.bg

Stefka Fidanova received M.Sc. Degree in Applied Mathematics and Ph.D. Degree in Computer Science from Sofia University "St. Kliment Ohridski", Bulgaria. She works as a Full Professor in the Institute of Information and Communication Technologies at Bulgarian Academy of Sciences. Her main fields of research are combinatorial optimization, mathematical modeling and parallel computing.