An Agent-Based Model for Emergent Opponent Behavior

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Abstract. Organized crime, insurgency and terrorist organizations have a large and undermining impact on societies. This highlights the urgency to better understand the complex dynamics of these individuals and organizations in order to timely detect critical social phase transitions that form a risk for society. In this paper we introduce a new multi-level modelling approach that integrates insights from complex systems, criminology, psychology, and organizational studies with agent-based modelling. We use a bottom-up approach to model the active and adaptive reactions by individuals to the society, the economic situation and law enforcement activity. This approach enables analyzing the behavioral transitions of individuals and associated micro processes, and the emergent networks and organizations influenced by events at meso- and macro-level. At a meso-level it provides an experimentation analysis modelling platform of the development of opponent organization subject to the competitive characteristics of the environment and possible interventions by law enforcement. While our model is theoretically founded on findings in literature and empirical validation is still work in progress, our current model already enables a better understanding of the mechanism leading to social transitions at the macro-level. The potential of this approach is illustrated with computational results.

Keywords: Opponent behavior · Opponent networks · Multidisciplinary · Complex adaptive systems · Agent-based modelling

1 Introduction

Terrorists, insurgents and criminals are typical examples of opponents or opponent organizations, as their actions may destabilize societies and endanger democracy and peace [28]. Efforts to intervene and control the behavior of these groups can also cause undesired effects like retaliation, escalation and displacement [39]. Therefore, understanding the dynamics of opponent organizations (e.g. growth, decline, merging, splitting) is essential in order to maintain a stable society [3, 39]. This dynamic behavior can be seen as a multi scale phenomenon emerging from multifaceted individual and societal interactions [37]. In fact the

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complex interactions between the different systems such as opponent organizations, law enforcement agencies and the society [39] yield the basic elements of complex adaptive systems (CAS): self-organizing, emergence, feedback loops, adaptive realignment and non-linearity [12, 23]. On a micro-level, *individual people* interact and act relatively autonomous. Nonetheless, different relationships, such as kinship, social, cooperation and financial, connect the individuals. [5]. These networks enable communication and autonomous cooperation, which yield self-organizing behavior of the individuals (at the micro-level). These local interactions yield emerging organizational behavior (meso-level). For instance, cooperative actions by individuals aim to generate synergy and establish a competitive edge over rivals. At a meso-level, these seemingly in-articulated individual actions, yield a structure that enable opponent organizations to execute violent actions and/or access to financial and other resources. As the opponent organizations are embedded in the society (macro-level), observations of events by individuals will influence the intrinsic, self-organizing behavior of individuals and groups. The economic situation or the intensity of law enforcement actions can yield positive and negative feedback loops. For instance, a bad economic situation can trigger opponent behavior as the scarcity of economic opportunities can nudge people to capitalize opponent opportunities (opportunities that enable opponent behavior are referred to as opponent opportunities). On the other hand, an increase of law enforcement activities is a typical example of a negative feedback loop as it reduces the attractiveness of opponent behavior [10]. These negative feedback loops constrain the growth of opponent groups within the society [8]. Understanding these dynamics is essential in order to grasp the emergent opponent behavior.

In this paper we will explore how a complex systems perspective can provide new insights into the behavioral dynamics of opponent organizations. We introduce a modelling approach extending the above insights from complex systems, by integrating criminology, psychology and organizational studies within an agent-based modelling (ABM) approach. Instead of modelling organizations as a whole, we use a bottom-up approach wherein agents represent individuals with active and adaptive reactions and act driven by self-interest. The resulting model enables at a micro-level the analysis of evolution of individuals and their networks and their potential to form opponent organizations. At a meso-level it provides an experimentation analysis of the development of opponent organizations subject to the dynamics of the environment and possible interventions. Finally, it enables a better understanding of the mechanisms leading to social transitions at the macro-level.

In the next section we will provide an overview of related work. In Section 3 we introduce our modeling approach, while in Section 4 we describe in more detail the agent-based model. Computational results can be found in Section 5. Finally in Section 6 we discuss the research results and implications for future work.

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2 Related work

Within complex systems theory, behavioral dynamics by individuals and groups are described as social phase transitions [25]. A social phase transition could be, for instance, a dramatic change in the way groups organize themselves. These transitions, similar as phase transitions in physics, are triggered by either slow processes or small events, which breach the resilience of individuals or groups [42] or alter their motivations [43]. Current studies show promising results using ABM to analyze how interactions and networks of individuals cause social transitions at multiple levels of a system [38, 14]. These efforts, however, describe dynamics of a population in general not specifically focused on opponent behavior. Specific studies are focused on the resilience of criminal [10] and terrorist networks [24, 27, 6] using simulation to identify vulnerabilities of these networks. However, the authors of these papers are unable to account for the impact of complex behavior as they perceive a closed environment with a preexisting network [40].

ABM is a relatively novel method to study social dynamics in environments of conflict. In 2002, Epstein introduced ABM to study the emergence of civil violence resulting from political grievance [14]. This model incorporated heterogeneous agents (civilians and peacekeepers) with specific decision rules. Within the model, the civilian agents interact and decide upon a rebellion based on the legitimacy of the authority. This approach demonstrated the ability to study complex social dynamics through simulation. Cioffi-Revilla et al. provided an ABM with an extended population and government model to analyse the impact of different governance strategies on the potential onset of civil unrest [7]. Moon and Carley extended upon this approach, as they presented a multi-agent model with social and geospatial dimensions [32]. This approach introduced multilayered network models of social and resources dependencies between individuals in covert networks. This methodology enabled analysis of organizational structures and identification of individuals with a critical position for the functioning of these networks. The modelling approach proposed in this paper builds on these efforts by integrating fine-grained micro mechanisms and form hypotheses on the causal relationships that cause the emergent phenomena of opponent organization.

3 Emergent opponent behavior

Once opponent behavior, which conflicts with norms and rules of the society, emerges we experience changes at different scales. At a micro-level the change of individual behavior from social accepted to opponent and vice versa can be observed. At a higher abstraction level, groups of different sizes and with various activities emerge. Rational choice theory offers an economic approach to explain how individuals rationally select their actions [9] based on a trade-off of expected benefits and costs. Depending on the intrinsic motivation of the individual, benefits can be associated to acquiring tangible assets such as money, but also non-tangible assets like increase of respect or the spread of fear [13].

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3.1 Opponent opinions and actions

Psychological research of radicalization identify individual, group and mass mechanisms leading to justification and eventually encouragement of opponent behavior [29]. Empirical research has described two separate processes that lead to polarization between groups: developing opinions and enact opponent activities [30]. According to Pruyt et al. [35] and McCauley et al. [30] individuals navigate back and forth through states which can be described as neutral, sympathizing, justifying to moral obligation with regard to opinion and inactive, activist, radical, and terrorist with regard to activities [35, 30]. These individual attitudes are influenced by events at meso and macro-level [29]. At meso-level the growth of like-minded groups increases the perception of security by its members and creates obstacles for law enforcement interventions [18]. According to Ganor et al. [18] the extent of public support for an organization is an important factor to ensure the existence of the organization. To an extent, repercussions by law enforcement towards radical actions can create a breeding ground for justification of radical opinions. This can lead to an increase of individuals with radical opinions and stimulating polarizing developments. This phenom at the macro-level can be seen as a *boomerang* effect [36]. Research focused on deradicalization and disengagement reveal the importance of social and economic factors to trigger processes reverse processes [43].

3.2 Characteristics of individuals and their relationships

At micro-level, individual and cooperative activities are observable. Bichler et al. [17] focus on the networks structures of opponent organizations and demonstrated the importance of human and social capital for successful opponent individuals and opponent networks. Human capital consists of the information, skills and resources possessed by individuals that enable capabilities. Social capital are the *social ties* between individuals that enable them to contact others, share information and initiate cooperation. Carley [6] and Bright et al. [5] emphasize the existence of multilayered networks of social relationships to enable exchange of both tangible and non-tangible assets

Our rational agent model incorporates the psychological and social dimension. Figure 1 illustrates the adaptive individual reasoning in an opponent environment. Individuals perceive opportunities and threats by observing events in their social network and environment. Subsequently the individual (de)radicalizes based upon these opportunities, threats, their social interactions and individual success. This influences the radical opinion state of the individual, which is an aggregated factor that represents the attitude towards possible activities. Simultaneously this influences the perceived benefits and costs and thus the expected utility of possible actions. According to the rational choice theory, individuals select the actions with the highest utility. As individuals might have different radical states the perceived utility of their actions will be different.

Self-organization causes that these emergent processes and components are becoming more organized, which yields interdependencies that constrain the

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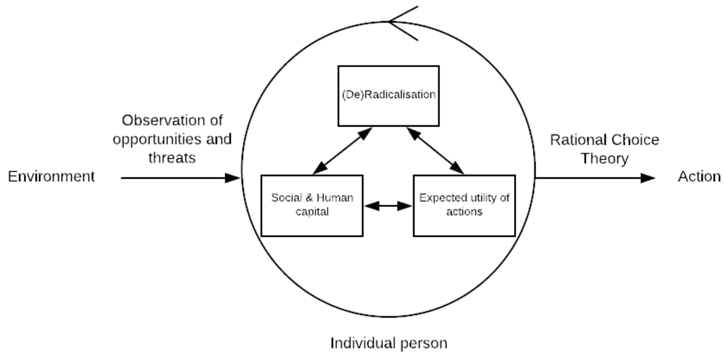

Fig. 1: Adaptive individual behavior

autonomy and controllability of the individual behavior [22, 34]. Furthermore, rational choice theory dependent on available information on opportunities and threats and influenced by the development of social ties and attitude enables us to model decisions that cause the social phase transitions, which we observe at multiple levels of our society [25, 42].

3.3 Dynamics of "collective" emergent behavior

The mechanisms underlying collective behavior of opponent individuals are illustrated in Figure 2. At the micro-level, individuals may cooperate and/or compete proactively or as a reaction to the environment yielding observable emergent organizational opponent behavior. Similarly to the rational decision making at micro-level, organizations also have specific goals, which should be achieved in the most effective way. As such we will use concepts of the field of organization theory, which focus on the deliberate and emergent strategies of cooperation, to analyze effective practises by opponent organizations [31].

The literature on opponent organizational theory is vast. In particular Framis [16] and Ligon et al. [26] describe a continuum of organizational sophistication. Respectively, this continuum from mechanistic to organic is characterized by a more hierarchical structure and a predictable design with a higher degree of formal rules and decision making, to a flatter structure and unpredictable design of cooperation described as a flexible network.

Whereas a lot of similarities can be found between common and opponent organizations, criminal, terrorist, and insurgent organizations are fundamentally differentiated due to the essential need for secrecy of operations [33]. Intensifying cooperation by opponents increases the chance of infiltration by law enforcement agencies or leakage of information [13]. The tension between the efficiency and security in this manner yield a trade-off while optimizing the effectiveness of opponent organizations.

Furthermore, opponent organizations often compete and become rivals [39]. Rios [36] describes a self-reinforcing equilibrium between rivalry by opponent

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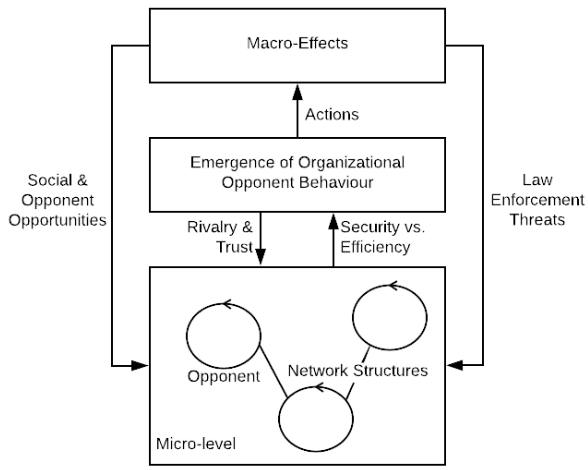

Fig. 2: Adaptive emergent opponent behavior

organizations, violence and law enforcement activities. Competition on illegal markets is unstable as they lack formal mechanisms, rules and institutes to cope with disputes, forcing participants to rely on trust [41]. Removing individuals and their relationships from illicit markets will create new power vacuums and a bigger unbalance within the market. Once organizational forms on illicit markets change from mechanic to organic, opponents become more individualistic and adaptive [36]. These dynamics increase competition and rivalry between the organized opponent groups.

The above drivers of organizational opponent behavior play an important role on top of of the individual adaptation and self-organization, which form the basis of our approach. In particular, the emergence of different opponent organizational structures depends on the feedback mechanisms of opportunity, threat and competition at micro and meso-level.

4 An agent-based model for emergent opponent behavior

The covertness of illicit operations hinders the possibility of extensive and detailed empirical research. Moreover, experimenting with interventions is both undesirable as it will disclose the strategy of the law enforcer as well as it hinders testing alternative intervention strategies. This is one of the motivations we have for promoting an in-silico agent-based simulation environment that allows us to conduct scenario-based experiments. These simulations provide insights into the nature of the underlying complex mechanisms and create a better understanding of the evolution of individual and organizational opponent behavior. Deriving outcomes of emergent behavior is impossible by a strict mathematical approach due to the amount of interactions, activity, decision rules, states, and

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variables etc. within this complex system [20]. An ABM offers the possibility to experiment and estimate the impact of the causal relations and parameters on the behavior of the system.

An agent-based modelling approach requires a computational representation of the theoretical psychological and behavioral concepts. We use paradigms of autonomous decision making, optimization and distributed systems and translate some psychological and economical theories into the agent-based model presented in this paper. Agents determine the expected utility of their actions to steer their behavior being either social or opponent, leading to a population of agents with different attitudes and (re)actions. Furthermore, our model incorporates typical ABM characteristics as the agents remember the results of their actions, observe and interact within their social network and environment.

4.1 Agent-based modelling

The purpose of our model is to understand how the interactions of opponents (individuals) under different conditions yield emergent behavior. Our simulation starts with a population of agents with a neutral attitude towards either social or opponent actions, which both 25 can yield a reward. These agents have to pay a certain amount of tax to their environment each time step, which they can earn through either social or opponent activities. The economic context of the environment has a scarce amount of social and opponent opportunities available for the agents to earn money to pay their respective taxes. Actions by law enforcement agencies (governance) pose a threat to opponent activity as they can disrupt opponent activities. This scarcity of opportunities compel competitive behavior by the individuals. At micro-level, the individual opponents operate by self-interest, autonomously and utility driven to mimic the rational decision making of opponents. To monitor the evolution of the system, different metrics have been identified from literature [4]: opponent density, ratio between opponent organizations and individuals, the average opponent organization size, the density of the cooperation by opponents and the effectiveness of opponent activity [33, 39].

Our model was implemented in NetLogo according the ODD-protocol to ensure the model is comprehensive and reproducible [20, 21]. The model consists of a population of agents and a contextual environment. The *environment* represents a two dimensional socio-spatial structure which mimics the complex mechanisms of the systems of society, economy and governments in reality. The environment yields adversity and competition between the agents. Law enforcement activities and the environment economic situation create challenges to the agents. Competition is forced by the scarce amount of resources that agents need to conduct either socially accepted or opponent behavior. The *agents* are embedded in underlying *networks*, which feature the functions of observation, communication and cooperation. These networks mimic relationships of people in reality [5]. The agents in our model are constructed according a BDI-framework to enable adaptive and reactive agent responses [19]. Movement and modification of networks enable agents to compete for an improved position. The agents

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are able to observe and conduct social and opponent activities individually or cooperatively with their associates.

4.2 Radicalization and rational choice

Various motives and attitudes were distilled from literature and modeled as agent states: *radical opinion state, desire state, intention state* [30, 43]. The radical opinion state represents the attitude of individuals towards opponent behavior. The desire state determines whether the agent aims to exploit social or opponent opportunity. The intention state determines how the agent aims to fulfill this desire, which in case of opponent behavior can be either individual or in a network or organization. Depending on the success of their activities and available opportunity, agents are rewarded for their actions. Agents can initiate bilateral cooperation to create synergy between two agents and increase their individual and collective effectiveness. In order to perform advanced forms of opponent activities, agents can initiate an *organization* to create additional synergy and extent cooperation.

A law enforcement agent is modelled to conduct *law enforcement activities*. These activities focus on specific agents that conduct opponent behavior and attempt to disrupt these activities. At each simulation time step, the modelled law enforcement agencies detect the opponent activities at a certain rate. They decide on the intensity of their counter actions and choose an action type: *direct countering* or *infiltration*. With a direct countering action, the most effective opponents will be countered. Successful counter actions will drop the reward of the opponent activity to zero. An infiltration action aims at uncovering opponents by infiltrating in the cooperation and communication networks of the initial known opponents. Subsequently law enforcement agents attempt to disrupt the opponent activities of one of the opponents detected by this infiltration.

The (de)radicalization process of individuals is modelled by incorporating three feedback mechanisms repeatedly found by empirical research [29, 1, 43]. The first mechanism to change the radical opinion state of an individual is caused by engagement and disengagement in activities [29, 43]. Whenever individuals conduct either social or opponent actions, their satisfaction (d_n) influenced by the reward of these actions, changes their attitude. For example, when an individual conducts a successful opponent activity their radical state increases and vice versa. This creates a positive or negative feedback. The second mechanism is found in studies towards social influence in radical groups [1]. The social network enables individuals to spread opinions and ideas, that ultimately drive individuals to create groups that think alike. The third mechanism is caused by the interaction between the individual, the society and the government [18, 15]. This mechanism, as outlined previously, causes that government actions against radical groups create a backlash in the deradicalization process of individuals with a radical attitude [18].

The radical opinion state is bounded by extreme values 0 (social) and 1 (radical). The radical opinion state of an agent on a given time ($r_{i,t}$) is the result of its opinion state in the previous time step ($r_{i,t-1}$) influenced by the satisfaction

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about the reward by activities (d_n), the average radical opinion level (r_{t-1}) of the communication network (G) of the agent and attitude towards law enforcement activities. By multiplying all these factors, the radical feedback factor ($s_{i,t}$) is obtained. Depending on the social (K) and communication (G) network of the agent, the radical opinion state of the agent is determined by the formula:

$$r_{i,t}(K, G, d_n) = \min\left(\max\left((r_{i,t-1} + s_{i,t}), 0\right), 1\right) \tag{1}$$

The radical opinion state effects the *expected costs* of opponent activities. The expected utility (U_i) of an opponent activity x by agent i (x_i) is given by the expected benefits (y_i) and costs (c_i). These benefits and costs are dependent on the cooperation network (H) and organization network (O) of the agent, which the agent can modify by negotiation with other agents in its communication network (G). The agents deliberately add or deduct cooperation links to control the density of their network, in order to increase the amount of synergy or to cope with expected law enforcement threat [11, 13]. The formula of rational choice behavior for opponent behavior is given by:

$$\max U_i(H, x_i) = y_i(G, H, O, x_i) - c_i(G, H, O, x_i) \tag{2}$$

The *expected benefits* of opponent activities (y_i) are based on the individual activity x_i, its chance of success (e_{d_c}), and activity of others (x_j) and the added synergy from cooperation (b_c) and added synergy from organization (b_j) in case the agents in the cooperation network of the agent (H) cooperate in one of both ways. In order to cooperate, agents need communication, such that $H \subseteq G$, with n amount of people in the respective networks. The level of crime activity of the cooperator equals x_j. Cooperation links are indicated by $h_{ij} = 1$, and are undirected.

$$y_i(G, H, x_i) = x_i e_{d_c}(1 + b_c * \sum_{j=1}^{n} h_{ij} b_j x_j e_{d_c}) \tag{3}$$

The *expected costs* of opponent activities (c_i) are based on the individual activity x_i and radical state (r_i). The vulnerability of the cooperation network (H) depends on the amount of law enforcement activity (d_{la}), their focus (f_{la}) and success rate (e_{la}). d_{la} and e_{la} are combined by multiplication yielding parameter s. The amount of law enforcement disruption attempts is determined by the law enforcement rate. The law enforcement focus will prioritise specific counter activities. The focus on effectiveness results in targeting the known opponents with the highest reward, which can be those who have the highest amount of connections, those with the most cooperation links or those at top of an organization. The infiltration focus will select one of the cooperation links of each of the potential targets. This causes an exponential risk for cooperation links as cooperation links are targeted by both policies. Fellow members of a organization ($\sum_{o=1}^{n} x_o$) pose an additional risk, as they attract attention from law enforcement and create an additional security breach in the network. As agents are aware of these potential counter measures, the following equation to calculate

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the potential costs is used:

$$c_i(G,H,O,x_i,r_{i,t}) = \frac{0.5}{r_{i,t}}(x_i + s(p(\sum_{j=1}^{n} h_{ij}x_j + x_i + \sum_{o=1}^{n} x_o) + q(\sum_{j=1}^{n} h_{ij})^2)) \quad (4)$$

A radical opinion state above 0.5 corresponds with justification of opponent behavior and will discount the envisioned costs of opponent activities. Once an opponent group grows, law enforcement has to focus on a larger group, which will discount the costs of the individual [15]. An optimum in the network will exist if $\frac{50}{r} + s > b_c$, as increase of costs by the addition of cooperation links will exceed the benefits. The parameters for optimization of the networks, other than $\sum_{j=1}^{n} h_{ij}$ are updated in the belief stage of the BDI-agent framework. If beneficiary, an agent will attempt to add cooperation links by negotiation with neighbours. Other agents use an equal procedure in order to consider whether addition of cooperation links is beneficial.

5 Model Analysis and Experiments

Social based computational models require validation to estimate the value of the model output [2]. We both verified and validated our agent-based model in order to analyze the accuracy and applicability of the computational model [20]. Predictive ABM requires *real-world data validation* to test whether the model output can be generalized to situations in reality. The intended application of our current computation model is to explore the effects of complex adaptive system mechanisms that underlie emergent opponent behavior. Validation against empirical data is still work in progress, that will allow us to test the predictive power at a later stage. Nevertheless our model demonstrates implications of the mechanisms that underlie emergent opponent behavior. Therefore a validation process for our computational model was conducted at the dimensions of *internal validity* and *methodological validity* [2]. The estimated validity concerns the value of input parameters to construct experiments, model concepts to explore complexities and sensitivity of the input parameters upon the output values. As a result, the model should be applicable and interpretable. The initialization of our experiments demonstrates the power to explore behavior under different scenarios and study the influence of environmental context to possible emergence of opponent groups.

The experimental design includes scenarios which varies the opportunity for social and opponent behavior, the intensity of the law enforcement activities and vary the focus of these activities. Using our simulations the following metrics were collected: amount of active opponents, opponent cooperation density, amount of opponent organizations and the collective effectiveness of opponent activity by individuals. Most interestingly we were able to distinct some expected and unexpected behavioral transitions in the system based upon our model.

The simulation results indicated social opportunity as the most important factor to influence the attitude towards opponent behavior (Figure 3). The output of the model describes a social phase transition of the system from a society

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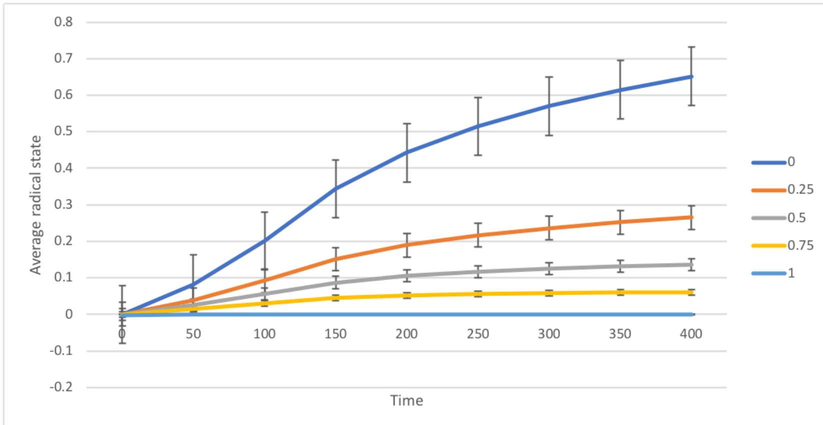

Fig. 3: Average radical state of agents by various amounts of social opportunity

with a low breeding ground for opponent activities towards a society with a high probability of justification of opponent behavior. This transition can be explained by the feedback mechanisms for individual satisfaction and social influence. However, the average radical attitude remained stable in scenarios with different amounts of opponent opportunity. Due to the scarcity of social opportunity, the agents are unable to satisfy themselves conducting social activities. Thus individuals will not deradicalize by government efforts to decrease the amount of opponent opportunity.

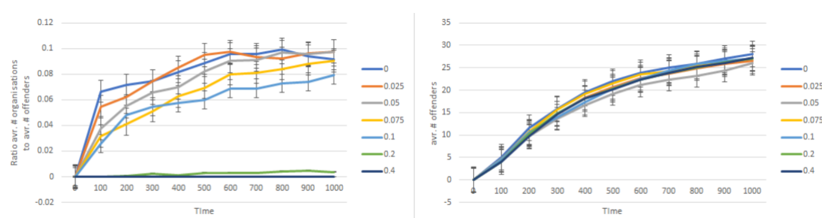

Fig. 4: Simulation results of random network initialization of 200 agents. Various intensities of law enforcement activity cause different organizational behavior; while the average amount of individuals that yield opponent behavior remains stable in different scenarios, there appears to be a transition in their collective behavior.

The metrics of the amount opponent organizations and opponent cooperation density also show interesting results. Notably the amount of opponent organizations decline as the rate of law enforcement activity to opponent activity increases from 0.1 to 0.2 (Figure 4), while the amount of opponents remain stable. They either operate in an organization or, as law enforcement activities threaten their operations, they operate in a loose network to deal with the increased scrutiny. This indicates that the organization process which determines

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the amount of cooperation and organization form might be constrained and subjective to a threshold set by the context in which it takes place [34, 22]. The spikes and slope in the diagram indicate quick and gradual social phase transitions by agents in organizational manners, which shift from mechanic to organic and vice versa. These organizational manners are influenced by the social network and radical opinion state of the agents and subject to the opportunities and threats posed by the environment. While opponent behavior is subjective to these factors, the experiment demonstrates that the behavior remains relatively unpredictable and resilient to changes by the law enforcement agencies.

Additionally, the ratio of organizations and their size were evaluated under scenarios with different strategies by law enforcement agencies, which either target the most effective opponents or infiltrate networks. The increased amount of organizations compared to loose networks shows the capability of individuals to adapt to the law enforcement infiltration strategy. Although the emergent behavior changes, the average effectiveness of opponents remained relatively stable. This demonstrates the resilience of opponents to disruptive strategies and complexity of analyzing and mitigating opponent behavior.

6 Discussion and Future Work

The emergent behavior of opponent organizations is a challenging topic in academic research and practice. The covertness of opponent activities and the fact that one cannot experiment with interventions in actual social systems without impacting that system have led us to develop and use in silico experiments that allow us to test the effectiveness of alternative intervention strategies and comparing the results. Our computational model provides an opportunity to experiment and uncover potential effects of governmental behavior when intervening in a social system with opponents. The ability to reveal complexities regarding opponent behavior using an interdisciplinary approach, and the computational agent-based modelling approach allowing us to study mechanisms relevant to subversive organization, such as competition and law enforcement are the main contributions of our developed methodology.

Our proposed approach provides tools to model the fine-grained evolution from the level of an individual. For future research we aim to extend the current components of our agent-based modelling efforts. We intend to include additional attributes of learning, psychological models and advanced game theoretic based behavior in a next version of our model. We then could for instance be able to experiment with scenarios where agents aim to minimize the utility of their competitors rather than maximize their personal utility or memorize past events and attempt to learn from the evolvement of past time interactions.

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