Agent-based modeling of social conflict, civil violence and revolution: state-of-the-art-review and further prospects

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Abstract. In this paper, we present a state-of-the-art review of Agent-based models (ABM) for simulation of social conflict phenomena, such as peaceful or violent street protests, civil violence and revolution. First, a simplified characterization of social conflict phenomena as emergent properties of a complex system is presented, together with a description of their macro and micro levels and the scales of the emergent properties. Then, existing ABM for simulation of crowd dynamics, civil violence and revolution are analyzed and compared, using a framework that considers their purpose/scope, environment representation, agent types and their architecture, the scales of the emergent properties, the qualitative and quantitative understanding of the phenomena provided by the results obtained from the models. We discuss the strengths and limitations of the existing models, as well as the promising lines of research for filling the gaps between the state-of-the-art models and real phenomena. This review is part of a work in progress on the assembling and dynamics of protests and civil violence, involving both simulation of the assembling process and the protest dynamics, as well as data collection in real protest events, and provides hints and guidelines for future developments.

Keywords: Agent-based modeling, Social simulation, Protest demonstrations, Civil violence, Revolution.

1 Introduction

Large protest demonstrations have been a powerful instrument for people to demand and sometimes achieve political change. Rulers and governments fear the "power of the crowds" [1]. This fear has been amplified by the protesters using Social Media Networks (SMN) and mobile communication devices to summon, coordinate and publish images and videos of ongoing events in almost real time to a worldwide audience [2], [3].

Recently, we witnessed large street protests, sometimes involving violent confrontation, e.g. in Greece. In Turkey, a triggering event (the plan to eliminate the Taksim Gezi Park in Istanbul) caused a major civil uprising with enduring violent confrontations between protesters and police forces. In Brazil, the increase of public transportation ticket prices lead to a series of violent protests. The massive revolution movement known as the "Arab Spring" already caused many deaths in violent confrontations between protesters and the police and military forces and lead to the fall of regimes in Tunisia, Libya and Egypt. Syria is currently in a state of civil war. Widespread access to Information and Communication Technologies (ICT), SMN and smartphones dramatically changed the dynamics of social conflict phenomena [2], [4]. The importance of understanding and if possible predicting and eventually controlling the trends in the number, variety and intensity of these phenomena cannot be overemphasized.

Social conflict phenomena are extremely heterogeneous and varied. Figure 1 shows an attempt to classify social conflict phenomena using intensity as a criterion and showing the scientific disciplines in which they are mainly studied. It should be mentioned that not only the conflict manifestations but also the overlaps and types of approaches shown in Figure 1. For instance, protests in the low end of the "intensity spectrum" can be carefully organized. However, the assembling in many of these events involve many individuals linked by networks, which after joining the protest display complex collective behavior in the spread of a variety of actions (waving, shouting, or even violent confrontation) which can be considered emergent properties resulting from general interaction rules. Thus, the problem can be studied using ABM and the tools from complex systems studies.

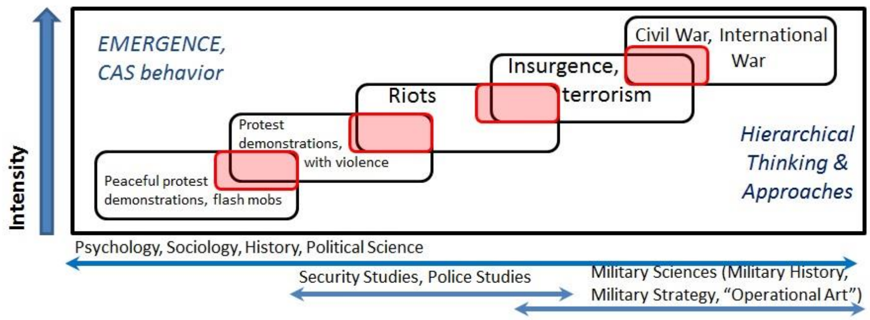

Fig. 1. Classification of Social Conflict phenomena based on their intensity (or level of violence) and the disciplines in which they are traditionally studied. Transitions between different manifestations of conflict phenomena are represented by gray rectangles.

Following the introduction of social simulation in the study of a wide range of topics such as opinion dynamics [5], the formation of culture [6] and segregation [7], several ABM were proposed for the simulation of civil violence [8], [9], confrontation between two rival groups [10], riots [11] and combat [12]. A review of formal approaches to the simulation of social conflict can be found in [13].

In this work, we present a state-of-the-art (SOA) review of ABM for the simulation of social conflict phenomena which we found the most useful in the context of an ongoing work on ABM of protest demonstrations and the conditions in which these can turn into violent confrontation. The remainder of this paper is organized as follows. In Section two, we present the theoretical framework for analyzing, comparing and discussing the models. This consists of: *i*) a conceptual characterization of protest demonstrations by means of three levels – the macro, or social context level; the micro, or agents' level and the level of the protest itself – considered as an emergent property of a complex system; and *ii*) a simplified scheme for analyzing and comparing the various models. Section three contains a review of the ABM according to the scheme described in Section two. In Section four, we discuss the strengths and limitations of existing models as well as the gap between model results and the dynamics of real-life protests. In Section five, we present the conclusions and discuss possible improvements to the SOA that we expect form our ongoing work.

2 Theoretical Framework

Protests occur when the social context leads to significant levels of grievance in a large proportion of the population and rises the level of internal conflict within the society. Triggering events lead to summon a protest at one or more places either by organizations (organic protests) or by groups of activists (inorganic protests). People may become aware of the protest by several sources and the decision to join the protest can be viewed as a contagion process. Once assembled, the protest may remain peaceful, or part of the crowd may engage in violent confrontation with police forces. Depending on the intensity of the social conflict and the grievance level the protests may persist in time or repeat cyclically, which in turn changes the social context. This qualitative description of protest demonstrations and their relation to the social context and the individuals (agents) is depicted in Figure 2.

Understanding these processes leads to questions such as: *i*) Why do some protests gather a huge number of people whereas others to not? *ii*) Which factors lead to initiation of violent confrontation and once initiated does it involve a large proportion of protesters? *iii*) What is the influence of ICT and media coverage on the dynamics of the protest? *iv*) How can police tactics in protest demonstrations be modelled? *v*) What is the influence of enduring or cyclical protests on the social context? *vi*) At a global scale, how can revolution (sudden change of political context) be modeled?

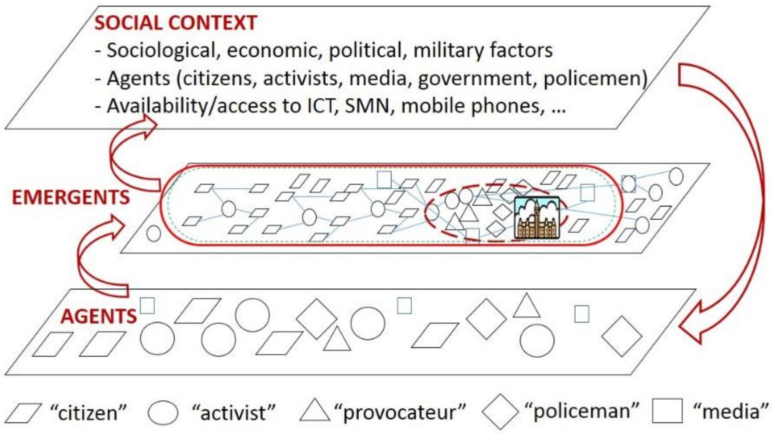

Fig. 2. Protest demonstrations and their relation with the macro (social context) and micro (agents) levels. The top layer represents the macro-level factors that influence social conflict. The bottom layer (micro-level) represents the relevant types of agents. The middle layer represents an ongoing protest, viewed as an emergent property. People joining the protest are represented within the solid line. Part of the protesters may engage in violent confrontation with policemen which may be protecting an important area (e.g. government building).

ABM can be described and analysed according to several schemes. The "Overview, Design Concepts and Details" (ODD) protocol [14] is one of the most popular methods, but full compliance with its specifications would be impractical for this review. Therefore, we devised a simple framework for presentation and comparative analysis of the ABM. The elements of this framework are listed in Table 1.

Table 1. Framework for comparing the ABM of social conflict, civil violence and revolution.

Description	
Purpose	Scope of the model (type of phenomena to be simulated).
Entities	Agent types (attributes, rules; reactive or deliberative) and environment (homogeneous or non-homogeneous).
Basic time cycle	Time cycle, sequence of operations, synchronous or asynchronous activations of agents.
Model results	Phenomena explained, scales of emergent properties (time, proportion of the rebellious agents, event inter-arrival time, etc.).
Observation	Use of empirical information for parameterization/validation.
Model strengths and limitations	Explanatory power; gaps between model results and real events.

3 Review of ABM of social conflict, civil violence and revolution

ABM of social conflict typically involve several agents representing elements of the population and law-enforcement forces (policemen), although models of revolution may include other types of agents, such as a central authority (government). Agents representing the population can have different characteristics (activists, troublemakers, passive ones) and change state (quiet, rebellious, jailed) according to their internal state and information sensed within their "vision radius" (neighborhood) and actions by other agents. In most ABM agents interact in grid or torus space objects.

The agents' behavior is described using either rational behavior model, in which the agents maximize a utility function, or (more frequently) the rule-based model, in which the agent's actions or state changes are described using simple threshold-based rules. This is illustrated in Figure 3.

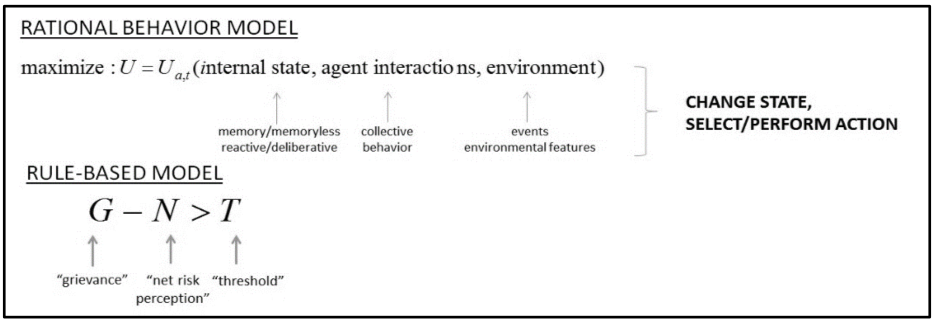

Fig. 3. In most conflict models, the decision of a generic agent *a* is based on the maximization of a utility function $U_{a,t}$ (rational behavior model) or the application of threshold-based rules (rule-based model) at each time step *t* (or cycle).

3.1 Threshold-based models of collective behavior

Social conflict, civil violence and revolution ABM are inspired on classical models that use simple threshold-based rules to represent collective behavior and contagion effects, such as Schelling's model of segregation [7] and Granovetter's model of collective behavior [15]. Granovetter's model is a theoretical description of social contagion or peer effects: each agent *a* has a threshold T_a and decides to turn "active" – e.g. join a protest or riot – when the number of other agents joining exceeds its threshold. Granovetter showed that certain initial distributions of the threshold can precipitate a chain reaction that leads to the activation of the entire population, whereas with other distributions only a few agents turn active.

Another model worth mentioning is the Standing Ovation Model of Miller and Page [16], which can be used to describe some dynamical aspects typical of real protests, such as the protesters applauding a speaker or the shouting of slogans within the crowd.

3.2 Epstein's model of civil violence (2001, 2002)

Epstein's model [8], [9] is the most well-known and widely cited model of civil violence. The purpose of the model is to simulate rebellion against a central authority (Model I), or violence between two rival groups (ethnic violence) which a central authority seeks to suppress (Model II). There are two types of agents: population and cop (authority) agents. In the case of ethnic violence, the population is split between two different types.

Both population and cops are defined as reactive agents driven by simple rules [17], [18]. Population agents can be in one of three states (Quiet, Active or Jailed). The attributes of population agents are position, vision radius v and a small number of parameters that characterize their political grievance G, risk aversion R, and threshold for rebelling T. The cops' attributes are the position and a vision radius v^* which may be different form v. Tables 2 and 3 summarize the attributes and rules for the agents.

Table 2. Attributes of "population" agents in Epstein's civil violence model [8], [9].

Description	Parameter name	Values(see [9], Run2)
V	Vision radius	1.7
H	Hardship	$\sim U(0,1)$
R	Risk aversion	$\sim U(0,1)$
G	Grievance	$H \cdot (1 - L)$
T	Threshold	0.1
J	Jail term	$\sim U(0, J_{max})$
(x,y)	Agent position in space	([0,39], [0,39])
Agent state	Q, A, J	Quiet, Active, Jailed

Table 3. Rules for population and cop agents in Epstein's civil violence model [8], [9].

Description	Notes:
Agent rule ***A***: If $G - N > T$ be Active; otherwise, be Quiet;	P = arrest probability
Cop rule ***C***: Scan all sites within v^* and arrest a random active agent;	Cops don't change state
Movement rule ***M***: Move to an empty random site within your vision radius	Identical for both types

In Table 2, L is the (homogeneous) perceived legitimacy of the central authority and in Table 3 the net risk term N is the product of the (heterogeneous) risk aversion R by the estimated arrest probability P:

$$P = 1 - \exp(-k\lfloor C/(A+1)\rfloor_v) , \tag{1}$$

where $(C/(A+1))_v$ is the ratio between the number of cops and the number of active agents within the vision radius[1]. The arrest constant k is set so that for $C = 1$ and $A = 1$ the arrest probability is 0.9, which gives $k = 2.3$. Collective behavior (contagion) is modeled via the net risk term. The basic time cycle consists of randomly selecting an agent within the agents list and applying the two rules, until a specified number of steps (cycles) is reached or the user stops the simulation. The environment in which the agents interact is a 40×40 torus space. The space and time scales are indeterminate.

For certain combinations of parameters and forms of the arrest probability function, results obtained with Epstein's model qualitatively explain many features of civil violence and rebellion, such as: intermittent bursts of violence involving a large proportion of the population (punctuated equilibrium), individual deceptive behavior (aggrieved agents are Quiet near cops but turn Active when they move away), the effect

[1] The original expression in [8] and [9] is $P = 1 - \exp(-k(C/A)_v)$, but this original expression does not give solutions with intermittent bursts and leads to divide-by-zero errors when $A = 0$.

of repressive or insurgence tactics, and the effect of gradual or sudden variations in the legitimacy of the central authority and number of cops. In the case of violence between rival groups the model reproduces the formation of safe havens and the transition between stable coexistence between rival ethnic groups and genocide events. In [8] and [9] no empirical data were used for model validation and parameterization.

The strength and success of Epstein's model lies in its simplicity, in the relevance of the variables used for modeling the agents' behavior and in its explanatory power. However, it also has significant drawbacks, such as: *i*) the agents' movement is not realistic; *ii*) the modeling of cops' behavior is very crude; *iii*) the model parameters are not related to social context indicators[2]; and *iv*) cumulative (memory) effects from previous events do not change either the agents' state or the simulation parameters. These led to many other authors trying to improve the model in various directions.

3.3 The Iruba model of guerrilla warfare of Jim Doran (2005)

Doran [19] developed an ABM of guerrilla warfare for describing the dynamics of asymmetric conflict between a weaker force of insurgents and a stronger force supporting a political regime, which is specific to the high-end spectrum shown in Figure 1. The insurgent force is initially much smaller, but has higher mobility and uses guerrilla tactics ("hit-and-run" surprise attacks, such as ambushes) and the features of the terrain as well as the sympathy of the population. In this model the agents are guerrilla bands, regime bases and outposts and headquarters (HQ) for each side, which can make decisions.[3] The environment consists of a grid of 32 autonomous regions in which the forces have limited control and weapon resources. The population forms a pool for recruitment of both insurgent and regime forces, according to history effects ("attitude variables" by both sides). The time cycle consists of Attacks, HQ decisions, recruitment and movement. The model includes random effects to simulate the uncertainty of the outcomes of attacks (engagement) and the simulations show the spatial spread of the insurgency, the time variation of the number of insurgents and regime forces, and the final outcome (which side is defeated). This model lead to interesting conclusions, namely: *i*) for defeating insurgence, it is necessary to contain it spatially and exhaust the recruitment pool, and *ii*) it is necessary to prevent the positive feedback loop increase of the number of insurgents/increase of population support to insurgents/recruitment of new insurgents among the population. The limitations of the model include lack of movement by population, effects of different types of attacks and third party involvement..

3.4 The EMAS civil violence model of Goh et al. (2006)

Goh et al. [20] proposed an improvement of Epstein's model for civil violence between two rival groups. The environment is a 20×20 grid. Population agents can be Quiescent,

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[2] In [33] a statistical model for validating the qualitative findings of Epstein's model on the incidence of the outbursts was presented.

[3] This is an example of the "hierarchical approach" being applied to describe conflict in the high-end spectrum depicted in Figure 1.

Active or Jailed as in Epstein's model, and an agent can be killed by Active agents of the opposing group. The specification of the population agents includes the following improvements with respect to Epstein's: *i*) the tendency to revolt is expressed in terms of two attributes, grievance G and greed Gr and a time factor T_f weighting these attributes[4]; *ii*) the movement is performed according to specified strategies, which are improved by evolutionary learning; *iii*) the net risk modeling includes a deterrence term involving the maximum jail term[5]. In this model, arrest is not automatic. Instead, interacting Cops and Actives play an Iterated Prisoners Dilemma (IPD) game and an arrest is made when the Cop wins. Also, the jail term varies (increases) depending on previous arrests. After a maximum tolerable number of arrests, a life sentence or a fixed jail term is applied. This increases the realism of the jailing process [20].

The EMAS model produced interesting results, such as: *i*) grievance is the primary factor to the onset of rebellion (more than greed); *ii*) solutions showed punctuated equilibrium and deceptive behavior of the individuals (as in Epstein's model); *iii*) spatial interactions resulted in patterns of group clustering; *iv*) increasing the number of Cops and longer jail terms decreased the Actives ratio and the intensity of rebellion peaks.

This model has the advantages of providing more realistic descriptions of movement and jailing than Epstein's model and of including memory and learning effects in the agents' specification. However, it has the disadvantages of greater complexity and still does not include representation of other actions (e.g. applause) or the effect of formal or informal media (information exchange beyond vision radius) on the dynamics of events.

3.5 The Computational Model of Worker Protest by Kim and Hanneman (2011)

Kim and Hanneman [21] proposed a model of worker protest based on Epstein's Model I (rebellion against a central authority) that incorporates two very important factors known from social psychology research: *i*) the grievance is expressed in terms of relative deprivation (RD theory [22]) resulting from wage inequality and *ii*) group identity effects.

In this model the grievance is expressed as $G = 2\times|1/(1 + \exp(-D) - 0.5)|$, where D is the agent's wage minus the local average of the wage within the vision radius. Grievance is zero for non-negative values of D and increases sharply for small negative differences relative to zero, but less rapidly for larger differences. Agents' wages w are obtained from a normal distribution $w \sim \mathrm{N}(wD/2, (wD/6)^2)$ and inequality is set by the parameter wD. The resulting grievance distribution resembles an exponential distribution, very different from Epstein's [21]. The risk aversion is defined as $R \sim \mathrm{N}(1/2,\ 1/6^2)$, instead of $R \sim \mathrm{U}(0,1)$, which is possibly more realistic. Validation or parameterization using empirical data was not done.

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[4] The agent turns active if $NAI = T_f \cdot (H \cdot (1 - L)) + (1 - T_f) \cdot G_r - R \cdot P \cdot J_{max}{}^{J\alpha} > T$, where NAI is the Net Active Index, J_{max} is the maximum jail term and J_α is a deterrence term.

[5] Actives can choose between "avoid the cops", "stay if favorable" or "kill civilians"; Quiescents can "run from actives" and cops can "pursue actives" or "protect civilians". Strategies are represented using a 14-bit chromosomal representation and agents with weaker strategies learn from stronger agents by adopting better traits [20].

Group effects are included by endowing agents with two traits, "tag" $t \sim U(0,1)$ and "tolerance" $T \sim N(1/2,\ 1/6^2)$, used to label agents as "in-group" or "out-group". For agent i, an agent j within vision radius is labeled as "us" (in-group) if $|t_i - t_j| < T_i$. In the absence of tag-based group identity, the rule for changing state (from Quiescent to Protesting) is the same as in Epstein's model. If group distinction is taken into account, the condition $\#\text{in-group}_v > \#\text{out-group}_v$ must also be satisfied for the agent to join the protest (agents access risk and group support).

The advantages of this model are the introduction of sound principles from social psychology and more realistic modeling of grievance, risk aversion and peer effects. However, this model also shares important limitations with the Epstein model (homogeneity of the environment, unrealistic movement of the agents, etc).

3.6 The Davies, Fry and Wilson model of the London Riots (2011)

Davies, Fry and Wilson [11] developed a model of the London riots of 6th -10th August 2011 based on three components: a contagion model for the decision to participate, a model for the choice of the site and a model for the interaction between rioters and police. The purpose of the model was to gain understanding on the patterns of riot behavior and the allocation of policemen to neutralize these events. The model combines rule based simulation with statistical descriptions, and also incorporates objective data on deprivation based on published reports.

The environment consists of a list of i residential sites and j retail sites in the area of London where the riots took place. At each time step: *i*) one agent in residential area i decides to riot based on its deprivation ρ_i and a function of the attractiveness W_{ij} to riot at j, which is a function of the distance between its residential area and retail site j, the floor space and the deterrence expected at j;[6] *ii)* if the agent decides to riot, it chooses the retail area j where to go, based on an utility function that takes into account the distance between i and j, the attractiveness of j and the deterrence (which depends on the expected number of police agents at the chosen rioting site); and *iii*) it interacts with the police, and may be arrested with probability P (see Table 4).

Table 4 shows the model components and expressions used to compute the relevant terms. At each cycle, the model updates the number of agents rioting at each site, which may arrive or leave, or be arrested there by the policemen.

Analysis of this model leads to the following comments: *i*) the processes of assembling, site selection and interaction with police are considered in a consistent formulation; *ii*) assembling is modeled as a contagion process, site selection as a cost-benefit decision based on an utility function; *iii*) interaction with the police is treated in a form akin to Epstein's; *iv*) the space and time scales are well specified; *v*) the model incorporates data on deprivation for modeling the probability of individuals joining the protest and statistics of the events (time variation of the number of rioters at each location). Thus, this approach is very sound and well founded, but the model must be

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[6] The deterrence is expressed as $\exp(-\lfloor Q_j/(aD_j) \rfloor$, where Q_j is the number of police agents in j, D_j the number of rioters in j and a is constant. This expression is similar to the one used in the arrest probability term in Epstein's model.

reformulated for the case of protest demonstrations, and the effects of media coverage and detailed modeling of the police forces were not dealt with.

Table 4. Components of the Davies, Fry and Wilson model of the 2011 London riots.

Processes	**Model components** (analogy)	**Formulae**
Decision to participate	Contagion (infection)	P(individual i joins riot) = $\rho_i \sum_j W_{ij}/(1+\sum_j W_{ij})$
Choice of site	Retail (distance, attractiveness, deterrence)	$D_j = \sum_j R_i(t) W_{ij}(t)/(1+\sum_{j'} W_{ij'})$
Interaction with police	Civil violence	P(arrest in j in one step) = $1-\exp(-\lfloor Q_j/(aD_j)\rfloor)$

In the aftermath of the London riots it was suggested that mobile phones should have been shut down in the hot spots to hinder the rioters' capability of coordinating their actions. Casilli and Tubaro [23] used a variant of Epstein's model, considered variations of the vision range to emulate the "degree of censorship", and concluded that *i*) different values of the vision range lead to different patterns of violence over time; and *ii*) that censorship of ICT is not effective. This latter conclusion is questionable, for the use of some type of dynamic network model would have been more realistic in this case.

3.7 The Mackowsky and Rubin model of centralized institutions, social network technology and revolution (2011)

Mackowsky and Rubin [24] developed an ABM for studying the mechanisms of large-scale social and institutional change, as well as the influence of the level of connectivity on the size of the resulting cascades, in an attempt to explain phenomena such as the "Arab Spring". In this model, there are three types of agents: citizens (heterogeneous), a central authority (government) and non-central authority (police forces). Citizen agents have randomly assigned positions in a 40×40 torus lattice. Social networks are represented by subsets of selected agents within Moore neighborhoods of radius *r*. The decisions of citizens, non-central authority and central authority at each time step result from the maximization of utility functions that are sums of quadratic terms representing the squares between own preferences and the preferences of other agents or sets of agents, weighted by different coefficients.

The main results of Makowsky and Rubin [24] are: *i*) in authoritarian regimes, individuals tend to hide (falsify) their preferences from others; *ii*) increased access to ICT and social networking can trigger cascades of "preference revelation" which lead to social revolution; large social revolutions may lead to institutional revolution.

This model provides a conceptual explanation for the dynamics of large revolutions and allows for change of the preferences of central and non-central authorities. However, it also has drawbacks, such as: *i*) social networks are synthesized using Moore neighborhoods instead of more realistic topologies; *ii*) influence from multiple contexts (family, friends, etc) are not taken into account; *iii*) the agents' attributes are not as relevant as those used in e.g. Epstein's model.

3.8 A model of crime and violence in urban settings by Fonoberova et al. (2012)

Fonoberova et al. [25] used Epstein's model for the simulation of crime and violence in urban settings. The purpose of the model was to determine the number of police agents required to keep crime and violence levels under a certain threshold in urban settings. These authors investigated two important features of Epstein's model, namely the sensitivity of the results to the variation of the arrest probability function with $(C/\mathrm{A})_v$ and the influence of agents that never change state. The authors used the probability arrest function originally proposed by Epstein and three other functions for which the perceived risk is zero up to a certain threshold, followed by a monotonic increase. They considered grids ranging from dimensions 100×100 to 600×600 to simulate the conditions in small and large cities and compared the simulations results with datasets from the FBI on crime and violence in 5560 U. S. cities.

The main findings of these authors are: *i*) the proportion of law enforcement agents required to maintain a steady low level of criminal activity increases with the population size, the variation being nonlinear; *ii*) reducing the number of police agents below a critical level rapidly increases the incidence of criminal/violent activity (this result was previously found by Epstein [8], [9] and agrees with data); *iii*) violence in small cities is characterized by global bursts whereas in large cities such bursts are decentralized; *iv*) large intermittent bursts occur when the variation of the perceived risk is non-monotonic but not when the variation is smooth. The strengths of this model are the use of different risk probability functions, and the use of representative data sets.

4 Discussion

We will now discuss the ABM of social conflict, civil violence and revolution models reviewed above, considering the relationships between them and the mechanisms that have been successfully explained. Then, we will point out the gaps that exist between ABM capabilities and the description of real phenomena.

Table 5 summarizes some of the main characteristics of the ABM. In all models except the Davies et al. model [11] the space is a homogeneous 2D lattice. It is clear that Epstein's model played a central role in the subject, due to the simplicity and soundness of its formulation, and its capability for explaining many patterns of rebellion and civil violence processes. However, as pointed out in Section 3.2, it has drawbacks that other authors later improved in several ways, as shown in Table 5. It can be concluded that existing ABM are capable of describing (at least qualitatively) many key mechanisms of social conflict, civil violence and revolution phenomena. In particular, they can explain as how small or large bursts of violence can emerge intermittently from simple rules and how the cascade mechanism of preference revelation conduces to instability of authoritarian regimes when access to ICT is sufficiently widespread.

Table 5. Comparison of the reviewed ABM.

Author(s)	Model Type	Social context in agents' specification	Agent rules, movement	Main results	Scales (space, time)	Observation and Empirical validation
Epstein et al. (2001), Epstein (2002)	Civil violence	No	Simple threshold-based, random	Intermittent bursts of rebellion, deceptive behaviour, effect of variable legitimacy and #cops	Global (society) Indefinite	No
Doran (2005)	Guerrila warfare	No	Simple rules	Spatial spread, time variation and outcome of conflict	Global (society) 32-cell grid	No
Goh et al. (2006)*	Civil violence	No	Simple threshold-based, rule-based	Group effects, purposeful movement, more realistic protester/ police interaction	Global (society) Indefinite	No
Kim & Hanneman (2011)*	Worker protest	No	Simple threshold-based, random	Intermittent bursts, grievance as function of RD	Indefinite Indefinite	No
Davies et al. (2011)	Riots	Yes	Simple and determined by utility, determined by utility	Three step contagion/site selection/police interaction model, realistic results, validation	London area, five days	Yes
Mackowsky & Rubin (2011)	Revolution	No	Simple, no movement	Cascade of preference revelation, general mechanisms of social & institutional revolution, influence of ICT	Global (society) Indefinite	No
Fonoberova et al. (2012)*	Urban Crime and violence	No	Simple rule-based, random	Discussion of arrest probability function, agents with fixed state and difference between large and small grids	Global (city size) Indefinite	Yes

*models based on Epstein's model

However, there are still significant gaps for ABM to describe the dynamics of social conflict processes in a more realistic way. Some of these are: *i*) variables like the hardship and grievance must be related to the RD and obtained from data collected in real events or reliable datasets; *ii*) the assembling stage of a protest is a "contagion process" with multiple influences (family, friends, SMN, etc), not accounted in current models; *iii*) the realistic description of the dynamics of protests requires the definition of more types of agents (Figure 2), and more complex rules and behaviors; *iv*) the modeling of police tactics is treated in a very simplified way in existing models (police agents have definite tactics that vary according to doctrine and respond to command and have an hierarchical structure); *v*) the effect of formal or informal media is not taken into account in current ABM. Finally, the feedback of past events (protests, rebellion bursts, riots) on the social context and on the agents' is not well understood.

5 Conclusions and future prospects

In this paper we presented a review of existing ABM for simulating social conflict phenomena, as part of an ongoing work related to this important and timely subject. The analysis was oriented by the conceptual scheme sketched in Figures 1 and 2 and done using the framework shown in Table 1. This allowed us to set a new perspective on the problem as well as the key features of the modeling system we are developing, and to anticipate possible research trends in this area. In our work, we will try to implement a new perspective on modeling protest demonstrations as a two-step process – assembling and protest dynamics – using the same agents, but introducing new agent types for representing new roles.

The assembling process will be modeled as a multiple-context contagion process using layered networks [26] and an adaptation the two step threshold model of Watts and Dodds [27] with cumulative effects (such as in [28]). In this approach, each influence context is represented by a specific network. The weighting of the multiple influences will be done at each agent, which behaves like a "stack of nodes". In this way, influences between two nodes that are not connected in a particular context (e.g. elements of different families) can propagate through the entire network, with different tie strengths and/or cumulative effects. In this way, multiple influences (family, friends, SMN, Unions, etc.) can be represented, based on classical network theory, as in the work by Nunes at al. [29]. With this type of approach, we expect to achieve better understanding of why some protests summon huge crowds whereas other don't, as well as the difference between organic and inorganic protests.

For the protest dynamics model, we are implementing an extension of Epstein's model, with the types of agents shown in Figure 2. For this, we have already implemented Epstein's model in the REPAST J/Java platform, and performed a heuristic analysis of the conditions that allow large intermittent bursts of violence to occur, which provides further understanding of the sensitivity of the model to the form of the arrest probability function. To obtain a more realistic representation of protest events with possible violence episodes, it will be necessary to create an environment with attraction and repulsion points as well as time-varying stimuli (speeches, throwing of objects, etc.). A better representation of the agents' behavior (actions and movement) can be inspired in models for intergroup fighting [10] and crowd dynamics [30], which describe well agent interactions in small-scale phenomena. For the realistic modeling of the police forces, the approach followed by Ilachinsky [12] for ABM of land combat may be adapted to the modeling of law-enforcing agents. This approach has the advantage of taking into account the hierarchical nature of these forces and allows for more than one type of police agents (command and policeman).

For parameterization and validation of the model, we are collecting information at real protest events occurring in Portugal using questionnaires, as well as images and videos to allow crowd counting and infer rules about collective behavior and police tactics. The questionnaires contain elements for quantifying legitimacy and grievance.

The statistical processing of the answers relative to grievance factors will related to the Failed States Index indicators ([31], [32]). We will use findings in social psychology to develop the functional relationship between these factors and relative deprivation, to better characterize grievance in the real context. In the same way, the questionnaires will provide information on the proportions of different types of agent roles (organizer, active, passive) and the small group structure of people in protests.

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