Abstract Social and Political Systems Simulation
The Concept of the Space of Ideas and Object-Oriented Simulation

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Abstract: We present an abstract, discrete event model of interactions between organizational structures, using the agent-base modeling. The parameters of agents, like ability, corruption level, resources and lust for power are taken into account, among others. The aim of the simulation is to visualize the evolution of the organizations and the stability of the whole system. It is pointed out that the "steady state" of the model can hardly be reached. Instead, for most parameter configurations, the model enters in oscillations.

1 INTRODUCTION

The very beginning of the *organization theory* should be dated to Plato (427–347 BC), and then Socrates and Aristotle. The recent theory is rooted in concepts developed during the beginnings of the Industrial Revolution in the late 1800s and early 1900s. Important ideas have appeared at the beginning of the past century (Weber, 1948). The idea of the *system* appeared in behavioral sociology and other social sciences, see Gunnell (2013). Recall that system behavior is not just a sum of the behavior of its components (non-linearity).

The model presented here is an abstract one, not related to any real social or political system. Our aim is to simulate the interactions between some hierarchical structures and to see how stable the whole system is. So, the results should be treated as qualitative only. This kind of model refers to political, trade unions and business organizations rather than welfare or benevolent institutions.

The main goal of any political party is always to obtain power and nothing more. Political organizations act as a new agent, using its members as nothing more than a medium to achieve its goal. However, in this model the organization itself is not an active process (software object or agent). The organization macro-patterns are the result of the entity activities. Here an approach and tools similar to those of Raczynski (2004) are used.

In this work we use agent-based modeling (ABM). An interesting agent-oriented model, called the BC model, can be found in the article by Krause (2000). In that model, the agent attributes include "opinions", and the interactions between agents depend on the distance between their opinions in a non-linear way. Similar examples can be found in Latane and Nowak (1997), Galam and Wonczak (2000), Chatterjee and Seneta (1977) and Cohen, Kejnal and Newman (1986). Some quite interesting results, more closely related to the terrorism problem, are described by Deffuant et al. (2002).

Another, agent-oriented approach is used by Lustick (2000), in which the agents interact on a landscape. It is shown that macro-patterns emerge from micro-interactions between agents. An interesting conclusion is that such effects are more likely when a small number of exclusivist identities are present in the population. The simulation of other mechanisms of clustering is described by Younger (2003). That article deals with the creation of social structures in the process of food and material storage.

Some more general concepts of

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"computational sociology" and ABM modeling can be found in the article by Macy and Willer (2002). Other general recommended readings in the field are: Bak (1997), Cioffi-Revilla (1998), Gotts, Polhill and Law (2003), Axelrod (1997), Epstein and Axtell (1996) and Holland (1998). An interesting contribution on modeling the structure of the Osama bin Laden organization is included in a Vitech Corporation page (link: see References, Long, 2002).

Knoke (1994) supposes that the most important elements of political power are the relationships of influence and domination among social actors. Influence is the exchange of information about preferences and intentions; domination is the exchange of material sanctions to reward or punish compliance with commands.

The very basic and comprehensive text on the organization theory can be found in Daft (2013). The book contains classic ideas and theories, and real world practice. The problems and questions addressed are related to the growing bureaucracy, management ethical lapses, competitors, government, the environment and the structural changes needed. However, Daft does not consider modeling and simulation as an important tool in organization design.

Another, (ABM)-oriented approach can be found in Crowder et al. (2012) and Hughes et al. (2012). In these publications we can find notes on the potential advantages of the ABM approach in the field of organizational psychology.

Many models deal with the *survival of the societies*. Cecconi and Parisi (1998) simulate a survival problem in terms of individual or social resources storage strategies. Saam and Harrer (1999) simulate the problems of social norms, social behavior and aggression in relation to social inequality. Staller and Petta (2001) discuss the emotional factor in social modeling. They introduce the emotions as an essential element of models that simulate social behaviors. Stocker, Cornforth and Bossomaier (2002) examine the stability of random social network structures in which the opinions of individuals change. They show that hierarchies with few layers are more likely to be more unstable than deeper ones. See also Moss de Oliveira and Stauffer (1999) for a model of aging and reproduction. The problem of survival and self-destruction treated from the ABS framework can also be found in my Raczynski (2006).

Adamic and Adar (2005) address the question of how participants in a small world experiment are able to find short paths in a social network using only local information about their immediate contacts. On the email network they find that small world search strategies using a contact's position in physical space or in an organizational hierarchy relative to the target can effectively be used to locate most individuals.

From a newer publications we should mention the book edited by Edmonds et al. (2007). The editors aimed to present a flyover of the current state of the art. The papers are divided into three parts: model oriented, empirically oriented, and experimentally oriented. In the other publication of Edmonds (2012) we can find an analysis of the role and effects of context on social simulation.

Silverman et al. (2013), present a model of a human population which illustrates the potential synergies between demography and agent-based social simulation. Elsenbroich (2012) asks what kind of knowledge can we obtain from agent-based models. The author defends agent-based modeling against a recent criticism. Sibertin-Blanc et al. (2013) present a framework for the modeling, simulation and the analysis of power relationships in social organizations

The agent-based modeling is a powerful tool, very different from other modeling paradigms, mainly Systems Dynamics (SD). In SD we start from the interaction rules for the model variables and from the structure of the real system to generate the system trajectories. In the ABM the interactions between the global variables are unknown, and the model is constructed defining the events that may occur in the "life" of model components (agents). Some artificial intelligence, like the ability to take decisions and to interact with other agents can be added to the agent specification. The global behavior of the model, the trajectories of the model variables and their eventual relations are the **results** of the simulation. In other words, the agents form a system, which behavior is not just a sum of the actions of individual components. This is the property of non-linearity (see Schachter and Singer (1962)). Obviously, no differential equations are defined or used, like in SD. This is the great advantage of ABM simulation, because not all what occurs in the real system is governed by the differential equations (something difficult to understand by electrical engineers). An exhaustive comparison between SD and ABM has been done by Borshchev and Filippov (2004).

Our model is rather abstract and can hardly be validated for real organization in a quantitative sense. However, a qualitative comparison con real organization dynamics may be done. For example, the oscillatory pattern of the size of real competing political parties coincides with the results of our model,

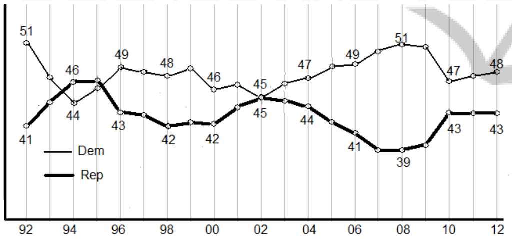

Figure 1: Oscillating nature of organization dynamics.

as shown on figures 1 and 3. The model can be used to get hints for the properties of the real system behavior. Note that the members of the model organizations move over a *political map* we introduce here. This map is a multi-dimensional "space of ideas", which coordinates may represent, for example, the level of "democratic orientation", "totalitarism", "religious orthodoxy" of the moving entities.

The concept of *corruption* in this paper should be interpreted in the very general terms. It may be an unethical/illegal behavior, or just a deterioration of certain ideological patterns or opinions. The corruption level can be associated with a spot on the political map. The main assumption is that corrupted spots provide little benefit to the model entities. So, the new entities tend to avoid these places. Blake (2005) considers rationalizations, which are mental strategies that allow employees (and others around them) to view their corrupt acts as justified. Another approach can be found in Pinto (2008), Lambsdorff (2012), or Earle and Spicer (2008). However, most of the academic papers on this subject are based on historic data analysis or psychological and social issues, rather than computer simulations.

An interesting, quantitative approach to the concept of corruption can be found in Caulkins et al. (2013), related to the earlier work of Schelling, (1978). Caulins et al. are looking for a "stable equilibrium levels of corruption" in their model. The point of equilibrium is found as a solution to an optimization problem. The decision makers or leaders are supposed to follow the solution to a linear-quadratic infinite time nonlinear optimal control problem. The model is continuous, and its dynamics is described by ordinary differential equations.

However, my point is that in the real world, and in particular in the dynamics of organizations with human factor, nothing obeys differential equations, and sometimes even a simple logic. So, the ABM model, where the only thing we define are possible events in the most elemental model components (members of the organization), seems to be more realistic. As for a possible point of equilibrium, its existence is rather questionable. The real organizations are in constant movement and hardly can rest in a theoretical "equilibrium point". See, for example, the data provided by PewResearch Center for the People & the Press, "A closer look at the Parties in 2012", available from http://www.people-press.org/2012/08/23/a-closer-look-at-the-parties-in-2012/ . Figure 1, taken from that article, shows the oscillatory nature of the dynamics of the main US parties, that coincides with the results of the presented model.

As our model provides qualitative results only, it can hardly be strictly validated, for example through input-output transformation. The **main point of this paper** is that the ABM modeling can provide interesting hints on organizational dynamics. The resulting model movement can be interpreted as the *orbital stability* known from the control theory, see Weinstein, M. I. (1986).

However, remember that no differential equations are used to describe the dynamics. So, the concepts of control theory, like stability, cannot be used here directly as done by Caulkins et al. (2013).

2 THE MODEL

Our model consists of three hierarchical structures interacting with each other over a common (abstract) region. Let us comment some terms used here.

Entity or agent. An individual that can be a member of a hierarchical structure.

Organization. A collection of entities, with a hierarchical structure. In this simulation no initial structure is imposed on the organizations. They are self-organizing, starting from the "chaos" (chaotic set of entities). Each organization has a ***corruption parameter***, telling haw corrupt or "spoiled" the organization is. The corruption level is calculated as the weighted average of the corruption parameters of all its members. The weight is equal to the reciprocal of the entity level in the organization. The head of the organization has level 1 (this is the level in the structure, not the corruption level), its subordinates have level 2, 3… etc.

Political Map (PM). This is one- or multi-dimensional region, where the entities are placed. The PM should be treated in a very general terms. It can be just a geographical region, or a generalized space of ideas or political orientation. For example, in a 2-dimensional case, one axis may be a religious orientation (from atheism to religious extremist), and the other may be the ideology (from democracy to totalitarism).

PM Corruption Field (CF). The political and social ideas are subject to wear. What was supposed to be a good idea a hundred years ago, is hardly considered as good now. The CF is a function of the spatial variable (position on the PM), that tells how "good" the spot is. It returns zero if the spot is completely spoiled and one if it is a good one. The value of CF is used by the entities that appear (are born, created) on the PM. It may also be used to control the random walk over the PM. The higher the CF is, the higher is the probability that the new entity occupies the place. This property of the spot on the PM may be the ideological deterioration (obsolete and erroneous trends and beliefs) or just a position that, after some time, no longer provides incentives and benefits to the entity.

Time. The model time is measured in abstract time units **(TU)**.

Entity personal data are as follows.

Ability. This is just the ability to climb in the hierarchy of the organization. Note that such concepts as intelligence or education do not exist in this model, being irrelevant in politics.

Lust for power. This is the most important entity parameter. In other words, the entity may become a leader if it really wants, which occurs in the real political life.

Resources. The financial or other resources that help the entity to climb in the hierarchy.

Corruption level. Takes values of honest to totally corrupt. The corruption level can be caused by the unethical/illegal behavior or other causes, like the rationalization tactics used by individuals committing unethical or fraudulent acts.

PM coordinates. The place the entity takes on the PM. In general, it is the entity political orientation. In our simulation the PM is two dimensional (mostly for the sake of image clarity) and its image on the screen is a square.

Life time. The life time determines when the entity dies or just disappear from PM (natural death). Life time is defined as a random variable with density function exp(70.0).

Superior. The pointer to another entity, the "boss". The entity is one of the subordinates of the boss.

Subordinates. Pointers to the subordinates of the entity. For the sake of clarity in the organization images, it is supposed that the entity should have four subordinates. So, if the number of subordinates is less than 4, the entity attempts to catch more subordinates. The *ability, lust of power, resources* and the *corruption level* are relative, with values in [0,1].

2.1 Interaction Rules

There are no global rules: the entities are being launched and what we obtain is the result of their individual actions. An organization is just a data structure and does not take any actions of its own. However, organizations behave as if they had a specific goal: grow and keep growing.

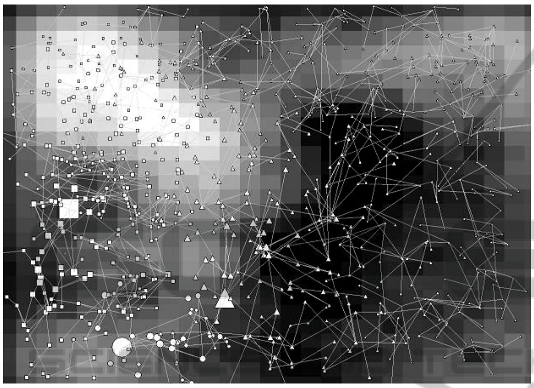

Figure 2: Dark PM spots - spoiled or corrupted area, white - "good" places.

The simulation program has been coded using the Bluesss simulation system. Recall that main concepts of Bluesss are *processes* and *events*. A process is a template, like a class declaration in object-oriented languages. At the run time objects (entities) are generated, being instants of the process declaration. Within a process a series of events are declared. The event execution is controlled by the Bluesss system, which invokes events in discrete time instants, according to the clock mechanism and to the internal event queue. For more detail consult http://www.raczynski.com/pn/bluesss.htm.

The model includes two processes: **entity** and **monitor**. The "organization" is not represented by any particular process; it is just a data structure. So, the organization itself has no "awareness" and does not take any actions. Model entities are created by the monitor process. After being created, the entity takes a place on the PM, due to a simple rule: the higher is the corruption level on the spot, the lower is the probability the entity will appear there. The monitor also initializes three organizations, marking three (randomly chosen) entities as organization heads, and nothing more. In this paper, the growing organizations have a simple hierarchical structure. The actions taken by the entities are as follows.

Seek for subordinates. At the very beginning, only the organization top entities (heads) seek for subordinates. This is done repeatedly, until the entity has gained four subordinates. Each of the subordinates starts to seek for their subordinates, and so on. Any entity that has its superior and less than four subordinates does it. The seek is based on the distance between the entity and its potential subordinates on the PM.

Die. This makes the entity disappear from the PM. The event occurs at the end of the entity life time. If the entity was a member of an organization, then one of its subordinates (say X, if any) takes its place. A subordinate of X takes the place of X and so on, iteratively. Note that the entity can also be "erased" by an action of one of its subordinates.

Climb. The entity eliminates his superior and takes its place. A subordinate of the entity takes its place and so on, iteratively. To be able to climb, the sum of the entity lust for power, ability and resources must be greater than the same sum of its superior. This attempt is permanently repeated.

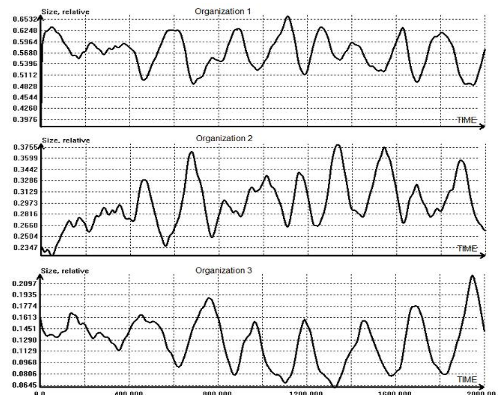

Figure 3: The relative size of the organizations as function of time.

Move. This is a slow random walk of the entity over the PM. The entity changes randomly its position by a small amount. The event is repeated every TU.

Propagate. The head of each organization propagates his own corruption level to all members of the organization. Each entity changes its corruption level as follows

entity_corruption_level = 0.1*head_corruption_level + 0.9*entity_corruption_level

This event is repeated each time unit. So, the corruption parameter within the organization becomes more uniform.

Modify PM. The entity changes the local value of the corruption field CF. The whole PM region is divided into 900 (30x30) square elements, each of them with its corresponding CF value. In this event a factor value is calculated using the following formula.

*F = (corruption_level/level + orgcorr)*0.04,*

Where *corruption_level* and *level* are parameters if the current entity, and *orgcor*r is the corruption level of the organization it belongs to. So, the entities with lower level value have less influence on the CF. The entity repeats this event each 0.5 time units.

The value of the CF is truncated to [0,1]. On the other hand, the CF recuperates constantly. The monitor process augments the CF in each spot by 0.015, each time unit. All this makes the CF change constantly, depending on how corrupt is the organization that occupies the spot.

3 SIMULATION

At the very beginning of the simulation run the monitor process is activated. It creates 1000 entities randomly located over the PM region. For each entity its parameters are being defined and the events *seek for subordinates, move, modify PM* and *climb* are invoked. The entity event *die* is scheduled to be executed at the actual model time (when the entity was created) plus the entity life time. If the entity has disappeared earlier, this event is ignored. The necessary events of the monitor process are initialized, like initiating organizations (mark the heading entities) organization state display, and CF recovery. The monitor process also stores the model state for further analysis and trajectory plotting. Then, all other events are executed automatically. The organizations grow, entities move and execute their own events. The situation after about 500 time units is shown on figure 2.

Organizations number 1,2 and 3 are marked with circles, squares and triangles, respectively. Small gray points represent new entities, not affiliated yet. The lines are links superior-subordinate. The big icon is the organization head, and the size of the icons decreases for entities with descending level. The monitor process shows the situation on the PM with small time steps, providing an animated image. It is a nice program feature, where the entities move over the area and the "spoiled" and "good" regions change intensity and move.

There are some possible scenarios for the model behavior. One could expect that the size of the organizations as well as the other variables will change chaotically. Another possibility is that one or two organizations will collapse and, after a long simulation time, and the strongest "winning" organization will remain. The experiments show that none of the above occurs. After a short initial transitory interval, the model enters in quite regular oscillations. Figure 3 (compare with figure 1) shows the relative size of the three organizations. In our model everything is stochastic, so every simulation is different. However, this oscillatory nature of the model can always be observed.

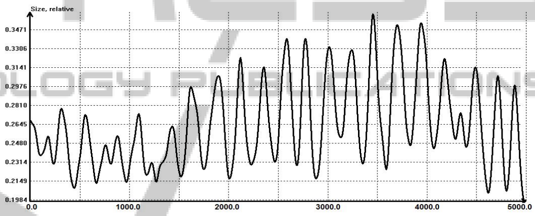

Figure 4: Relative size of organization 3 after longer simulation time.

4 CONCLUSIONS

The main conclusion is that no steady state is reached by the model and that the organizations are in permanent movement. This movement, after sufficient simulation time, is oscillatory, like the stable cycles in non-linear, orbitally stable dynamic systems (see Chen, 2004).. The model entities are "alive", executing their events. Though the decisions they take are very simple (where to appear on the political map, climb etc.), they can be considered as agents of an agent-oriented simulation. The model may provide interesting qualitative results. As mentioned in the introduction, the historical data from the real world are similar to those obtained from our simulations.

The important advantage of such simulations is the possibility of obtaining results that can hardly be reached by other (analytical, sociological) methods. For example, how can we see, from the model description, without simulating, that the organization size will oscillate with a period of about 208 time units ? Another advantage of the tool used here (Bluesss) is the open nature of the model. New events can be easily added to the entity process, reflecting a possible entity behavior and resulting in other, sometimes unexpected behavior of the organizations.

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