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Collaboration and Competition in Complex Environment – an Agent-based Approach

Tomasz Owczarek
Silesian University of Technology, Faculty of Organization and Management,
Zabrze, Poland, tomasz.owczarek@polsl.pl

Abstract— **The article is an attempt to apply complexity theory to study organizations in an environment filled with their competitors and complementors. An agent-based simulation is used to analyze effects of interactions in an environment with different level of complexity. Agents operate trying to adapt to fitness landscape they are placed in (which is based on Kauffman's *NK* model) and the obtained level of competition is observed. Results of conducted simulations are presented and analyzed.**

Keywords—agent-based modeling, NetLogo, complexity, competition.

I. Introduction

It is believed that growing complexity of business environment changes interorganizational relationships and the way organizations perceive their rivals [1]-[2]. New ICT technologies and rapid growth of internet as sales and advertising medium are main causes of the more and more comprehensive (and thus more complex) products and services offered by firms. For this reason organizations today cannot operate alone. Sometimes their main partner in some activity is at the same time one of the largest competitors in another. This can be a difficult situation which is shown e.g. by the case between Apple and Samsung [3]. This is why firms must wisely choose where to compete and where to cooperate and it is decision of strategic importance [4].

The term coopetition (which can be defined as cooperation with competitor) is getting more and more attention in strategic management [4]-[6], and different approaches are used to study this concept [7]. The article is an attempt to apply complexity theory [8] to study behavior of organizations in an environment filled with their competitors and complementors [5].

In the article agent-based model [9]-[11] is used to analyze effects of interactions in an environment with different level of complexity. In order to increase their fitness agents try to adapt to the fitness landscape they are placed in (which is based on Kauffman's NK model [12]) and at the same time they must decide where to compete with other agents.. The main purpose of the model is to answer the question about the impact of the environment's complexity on the level of competition established between agents.

The article is organizes as follows. Section two presents the *NK* model used as a representation of environment with desired level of complexity. Section three describes the details of simulation model. Results of conducted simulations are presented and analyzed in section four. Section five contains conclusion and directions for future work[1].

II. *NK* Model

In Kauffman's *NK* model [12] agents are treated as systems. They consist of fixed number of elements (parts). The combination of values of each element is agent's inner structure. The *NK* model is an abstract representation of a fitness landscape i.e. a mapping from an agent's inner structure to its fitness level. Agent's fitness strictly depends on its inner parts. The set of parts, in the domain of organizations, can be interpreted as elements of its business strategy, human resource policy [13], resources owned, product features and so on.

A. Formal Definition

There are two main parameters in the model. Parameter N refers to the number of elements each agent consists of. Greater N means that there are more types of different possible agents. Parameter K is responsible for the number of interconnections between the elements, because each element contributes some fitness but this contribution depends upon that element and upon K other elements. In the original Kauffman's model there is also additional parameter which specifies the number of possible values each element can have. In this paper it is assumed that each element can have two values: 0 or 1 so the number of all possible different agents is 2^N.

As it was said, each element s_i (i = 1,…, N) makes a fitness contribution w_i specified by *NK* model (usually it is a random value drawn from the uniform interval between 0.0 and 1.0) . The fitness of agent A is defined as the average contribution of its elements:

$$W^A = \frac{1}{N}\sum_{i=1}^{N} w_i^A \qquad (1)$$

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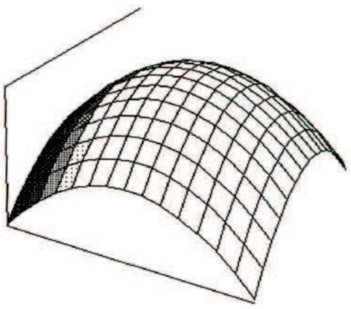
Table I shows two models with N = 2, first with K = 0 (model a) and second with K = 1 (model b). Two examples of agents and their fitness are also presented.

TABLE I. EXAMPLES OF *NK* MODELS

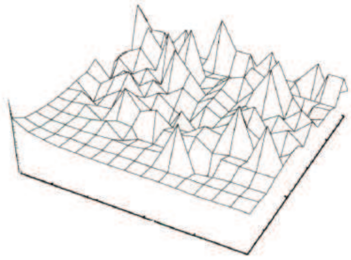
	elements	s_1 fitness	s_2 fitness
model a K = 0 (each element is independent)	(0, *)	0.6	-
	(1, *)	0.3	-
	(*, 0)	-	0.1
	(*, 1)	-	0.4
Example 1: $W^{(1,1)} = (0.3 + 0.4)/2 = 0.35$			
model b K = 1 (elements depend upon each other)	(0, 0)	0.4	0.8
	(0, 1)	0.7	0.3
	(1, 0)	0.5	0.9
	(1, 1)	0.6	0.5
Example 2: $W^{(1,1)} = (0.6 + 0.5)/2 = 0.55$			

B. *Landscape Ruggedness*

The main feature of *NK* model is the possibility of establishing desired *ruggedness* level [14] of the generated fitness landscape, which depends upon the parameter K. When K = 0 the surface of a landscape seems smooth, with single optimum which can be reached from any point by a series of local adaptations (Fig. 1a). When $K = N - 1$, the generated landscape is very rugged, with many local optima and a slight change in agent's structure can have a significant impact on its fitness (Fig. 1b).



a) smooth, single-peaked landscape



b) rugged, multi-peaked landscape

Figure 1. Different kinds of landscapes [13].

Consider examples presented in Table I. Changing the first element of the agent from example 1 will have a positive effect on its fitness (0.6 instead of 0.3) and it does not affect fitness contribution of its second element. The same change in the structure of agent from example 2 will decrease its overall fitness: it will increase the fitness contribution of its first element (from 0.6 to 0.7) but at the same time the fitness contribution of its second element will be worst (0.3 instead of 0.5).

Simply speaking, the more interconnections between elements of agent's structure (i.e. the greater value of K), the more complex is the environment it exists in.

III. SIMULATION MODEL

The simulation model was created and performed with NetLogo 4.1, a multi-agent programmable modeling environment [15]. The simulation consists of two steps: first the fitness landscape with specified parameters N and K is generated and then agents are placed in the landscape and they try to adapt (in order to receive the greater utility) by moving from one place to another.

A. *Fitness Landscape*

In the simulation model fitness landscape consists of 2^N nodes (called *places* in the model) which represent any type of agents' inner structure. Each place is connected with its one-mutant neighbors, i.e. places which differ only in one position. Places are the nodes of undirected graph and their position is based on the Fruchterman-Reingold layout algorithm [16] (function *layout-spring* in NetLogo). Each place has its fitness specified according to *NK* model described earlier.

Fig. 2 presents two examples of generated fitness landscape. For more clarity most of the links between places were hidden. The size of each place corresponds to its fitness level (greater size means greater fitness). Both landscapes were created with N = 9.

Fig. 2a presents smooth landscape (K = 0), places with smaller fitness are distributed in the upper-left corner. Two places were highlighted and their neighbors were shown. One can notice that the sizes of the connected places are very similar.

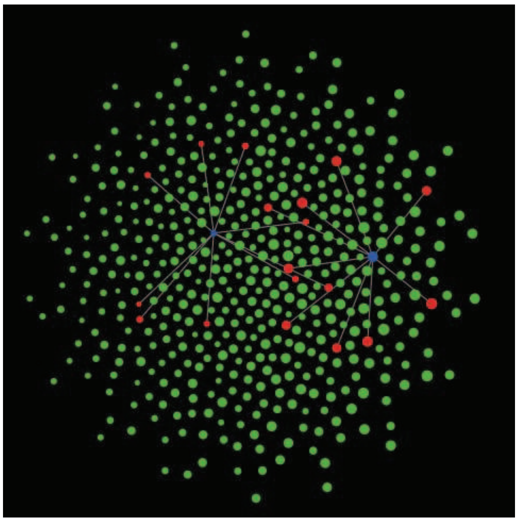
Fig. 2b presents a fitness landscape generated with parameter K = 8. Also two places were highlighted. This time there are noticeable differences between fitness levels of connected places.

B. *Agent Adaptation*

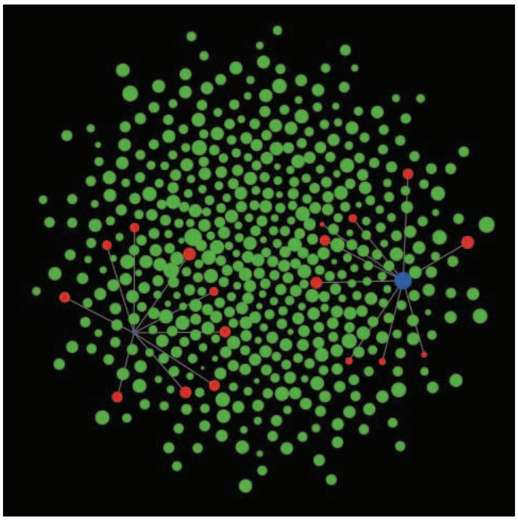
When the fitness landscape is constituted F agents are distributed in random places. A place occupied by agent defines the agent's inner structure and its fitness. Agent's utility (gain) from occupying a place depends on the place's fitness but it is also modified by level of competition. The level of competition c_i is defined as the number of agents with the same value at the i-th position of their inner structure. Consider two agents: A = (1,0,1) and B = (1,0,0). They are perceived as competitors at the first two elements and as complementors at the third element. Agents which are occupying the same place are seen as direct competitors.

Let w_i be the fitness gained from i-th element of the occupied place, let c_i be the level of competition at the i-th element and let F be the number of agents. Then utility of agent is defined as:

$$U = \frac{1}{N}\sum_{i=1}^{N}\frac{F - c_i + 1}{F} w_i \qquad (2)$$



a) $K = 0$



b) $K = 8$

Figure 2. Examples of fitness landscapes generated in the simulation model ($N = 9$).

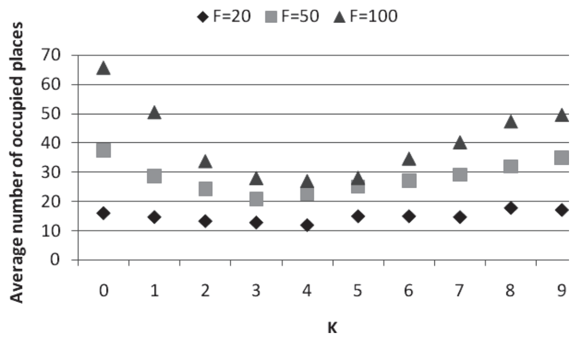
In each iteration agents calculate their current utility and check the potential utility of neighboring places. If the potential utility is greater than their current utility, they move to a new place.

Two variants of agents' behavior were considered. In the first, agents looked only at the fitness of a potential new place and compared it with their current utility (figures with results of this variant are labeled *rivals are not considered*). The presence of other agents was not taken into consideration. This was to illustrate that firms often do not have full picture of the level of competition of the market they are trying to enter. In the second variant agents use full knowledge about competition level when deciding whether to change place (label *rivals are considered*).

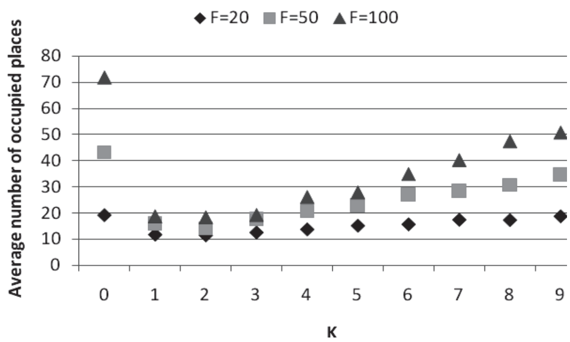
IV. Simulation Results

The simulations were conducted with different levels of parameters N, K and F. As it was described earlier, first two parameters are responsible for complexity of the environment. Different values of F were used to explore if the number of firms had any significant meaning.

In each series after a few iterations movement of agents' stopped (with few agents oscillating between two places). Different parameters were monitored but the most important is number of different places occupied by agents which can be considered as the level of established competition. Figure 3 presents the average number (from 10 series of simulation runs) of occupied places when $N = 10$, the number of agents F was 20, 50 and 100 and K varied from 0 to 9. Figure 4 presents the same results normalized to F which gives relative level of competition. Here 100% means the lowest possible competition (i.e. all firms occupy different places).



a) rivals are not considered



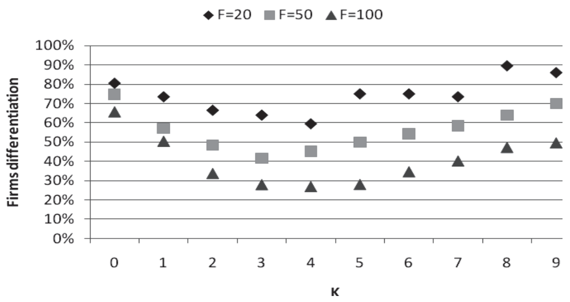
b) rivals are considered

Figure 3. Average number of occupied places in the simulation runs.

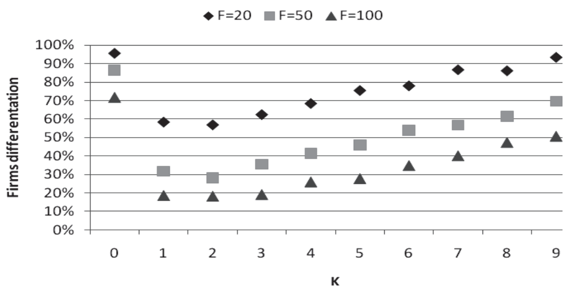
As one can see the relation between K and the number of occupied places is not linear. In both variants greater level of competition (i.e. less occupied places) occurs with moderate values of K, while the extreme values of K correspond with lower level of competition.

For K = 0 the differences between places are so small that the optimum is never reached because of the competition level.

For K > 3 the presence of many local optima stops firms from further movement.



a) rivals are not considered



b) rivals are considered

Figure 4. Firms differentiation in the simulation runs.

For K = 1, 2, and 3 there appear slight differences between the two variants considered. Figure 5 presenting average utility value helps to explain these differences. It seems that use of full knowledge about the competition level makes firms choose better "path" while selecting new places and this way they ends with higher utility.

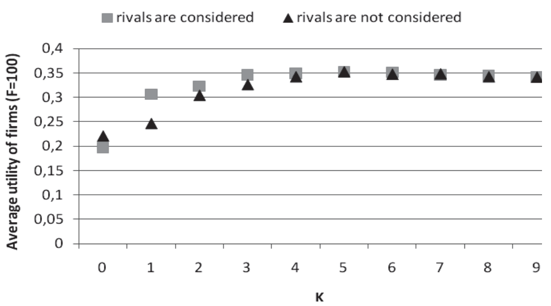


Figure 5. Firms differentiation in the simulation runs.

For K > 3 differences between the two variants disappear – ruggedness of the landscape causes that the method of choosing new place (and thus knowledge about current completion level) does not influence the utility gained by firms.

V. Conclusions and Further Research

The obtained results are very similar to the findings presented in [17]. One can assume that as far as complexity is considered the relationship between variables is not linear but rather U-shaped.

The presented model can be a base for further research. Firstly, it was assumed that each element of a place could have only two values. This assumption can be dropped to make the relationship between firms more sophisticated. Secondly, some direct interactions between firms can be added, e.g. with the use of game theory. Finally, differentiation in firms' behavior can be included, e.g. some firms could change their places in other way than the rest of them.

Acknowledgment

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