Using complex networks in social impact models

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This paper describes models of opinion dynamics. It presents various ways of modelling opinion spreading in the population. The author proposes to apply complex networks to a model, which is based on the theory of social impact. The agent based modelling is applied to construct the model and perform simulations. Performed simulations allowed to investigate how the use of complex networks and its properties have an influence on the final distribution of opinions in the population. The results of simulations have been shown and interpreted.

Keywords: social impact model, social simulation, opinion dynamics, complex networks.

1. Introduction

There has been an increasing interest in recent years in the study of models of opinion dynamics. The term opinion dynamics is wide and range from emergence of fads, minority opinion spreading, collective decision making, finding of consensus, emergence of political parties, emergence of extremism, rumour and fear propagation. The research of dynamic opinion models has become one of the mainstreams of new interdisciplinary field – sociophysics [1]. The sociophysics applies theories and methods originally developed by physicists in order to solve problems in the sociology. In the recently years researchers try to identify factors, which have a significant impact on process of changing an opinion by person. It causes that many models of dynamic opinion are developed. The most of those models use specific approach to construct a model and then verify the adequacy of these models. The model of dynamic opinion involves two elements: a population of individuals and a function of changing internal state of each individual. The population may refer to a small group for example work group or entire society. However, the individual is each person, who has internal features, which characterize psychological or physical predispositions of person. Individuals also act independently of others. Additionally, individuals have an opinion, which represents a belief of person based on thoughts and ideas with regard to specific subject. The opinion is an internal state of the individual. The process of changing opinion is a complex process affected by the interplay of different elements, including the individual predisposition, the influence of positive and negative peer interaction, the information each individual is exposed to, and many others. Based on nature of opinion space, the following models could be identified: model with discrete opinion space (classically binary opinions) and model with continuous opinion space (continuous opinion dynamics). This paper deals with models with discrete opinion space, but also review some models with continuous opinion space.

Based on this general introduction to opinion dynamic models, it can notice that agent-based modelling is used to construct model and to perform simulations. In this context term agent means individual and those terms may be used interchangeably. The agent-based modelling assumes that each agent acts independently of others and has internal features. Agents interact either directly or indirectly way through environment, which provides information about activities of the other agents. Every simulation step agent decides to change her internal state according to specified rules. The rule of changing state is a function depending on agent's features and activities of the other agents. The state of agent for opinion dynamic model is currently supported opinion. The simulation is used to test the adequacy of model. The appropriate technique for performing simulation for agent-based approach is a Multi Agent Based Simulation (MABS). The MABS is a kind of micro simulation.

The micro simulation attempts to model specific behaviours of specific individuals. It's contrasted to typical simulation techniques, which are based on mathematical models, describing whole population [2], [3], [4]. Thus, in macro simulations, the set of individuals is viewed as a structure that can be characterized by a number of variables, whereas in a micro simulations the structure is viewed as emergent from the interactions between the individuals. This methodology finds successful application in social simulation. An exhaustive presentation of agent based models is out of the scope of this paper. You could find an in-depth description of agent based methodology in [2], [3], [4].

The important element of dynamic opinion model is a environment. It is responsible for interacting between agents by modelling relations between agents. The environment is modelled as a network (graph) $G = (V, E)$, where V represents the set of nodes and E represents the set of edges. Each node corresponds one agent in network. Thus, each agent in the network directly or indirectly influences others in the network. The network is usually represented by social network in the dynamic opinion model. The social network shows friendships or user interactions in a social media. It is a complex network and has the following important features [1], [5], [6]:

a) an average distance between two random chosen node is small
b) a clustering coefficient is high. In most of applications, the structure of network is fixed and doesn't change during simulation. In this paper the structure of network is always fixed.

Some type of complex network such as small--world [7] or scale free [8], [9] are used in this paper.

The aim of this article is to present social impact model, which is extended by adding the complex network as the representation of relations between agents. The paper also shows how to initial location of agents has impact on the final distribution opinions by using the different kinds of complex networks. The author also reviews models of dynamic opinion in order to show the ways of modelling spreading of opinions.

The next section describes shortly different models of opinion dynamics. Then proposed model is presented and simulation results are discussed.

2. Models of opinion dynamics

There are a different kind of opinion dynamics models, but all of them propose new attempt to formulate the way of opinion spreading. The process of formulation opinion usually defines opinion states and elementary processes that determine transitions between such states. In the next subsections, four models, which occur frequently in sociophysics literature, will be presented.

Majority rule model

The majority rule model [10] is a simple model of opinion dynamics. It is suitable for modelling public debate. Let's consider a population of N agents. Each agent is endowed with binary opinion s, where $s \in S = \{+1, -1\}$. The set of all agents A is divided into two subset: A^+ and A^-, where A^+ represents agents with opinion +1 and A^- represents agents with opinion –1. All agents can communicate with each other, so the graph of contacts is complete graph. At each simulation step a group of r agents (P) is randomly selected with uniform distribution. As a consequence of the interaction between selected agents, all agents take the majority opinion inside group. This is the basic principle of the majority rule (Figure 1).

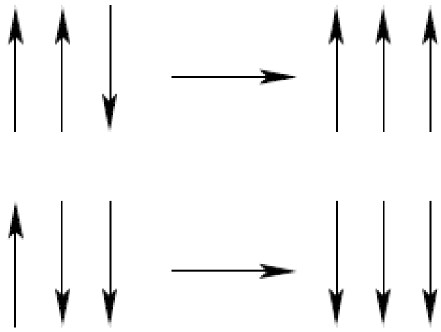


Fig. 1. The principle of majority rule model [1]

The majority rule model can be defined in the following way:

$$
\begin{gathered}
A = A^+ \cup A^-, |A| = N \\
A^+ = \{a_i : s(a_i) = 1 \; and \; 1 \le i \le N\} \\
A^- = \{a_i : s(a_i) = -1 \; and \; 1 \le i \le N\} \\
s: A \to S, S = \{+1, -1\} \\
P = P^+ \cup P^-, P \subset A, P^+ \subset A^+, \; P^- \subset A^- \\
|P^+| = k, |P^-| = m \\
|P| = r = k + m
\end{gathered} \tag{1}
$$

where:
A – a set of all agents
$s(a_i)$ – an opinion of agent i
P – randomly selected set of agents
r – a size of group, $|P| = r$

Following rules of changing agent's opinion are used at each simulation step:

- If $k > m$ then all agents $a \in P$ change their current opinions into $+1$:
  $$\forall a \in P^- \; s(a) = +1 \tag{2}$$
- If $k < m$ then all agents $a \in P$ change their current opinions into -1:
  $$\forall a \in P^+ \; s(a) = -1 \tag{3}$$
- If $k = m$ then agents $a \in P$ don't change their opinion. This situation is called as tie.
- If agents $a \in A \backslash P$ then their opinions aren't changed, because they don't take place in debate.

A group of r agent is some discussion group. This model applies to describe process of spread opinion in small group [10]. The factor r describing group size is not fixed but is defined by some distribution. Some researches show that if r is odd, there is no way of occurring a tie, because the size of one group (P^+ or P^-) is greater than the other group. If r is even, instead, there is the possible of a tie, because a size of P^+ and P^- may be equal. In this case, one of solution is to introduce a bias in favour of opinion $+1$ or -1 [1], [11]. There are many variants of the majority rule model that are described in [11], [12].

Sznajd model

The basic principle of Sznajd model is assumption that convincing somebody is easier for two or more people than for single individual [13]. Let's consider a population of agents with discrete opinions $S = \{-1,1\}$ and agents occupy a place of linear chain. A pair of neighbouring agents i and $i+1$ determines the opinions of their nearest neighbours ($i-1$ and $i+2$) according to two basic rules:

If $s_i = s_{i+1}$ then $s_{i-1} = s_i = s_{i+1} = s_{i+2}$ (4)
If $s_i \neq s_{i+1}$ then $s_{i-1} = s_{i+1}$ and $s_{i+2} = s_i$ (5)

The rule (4) and (5) are called ferromagnetic rule and antiferromagnetic rule, respectively. According to ferromagnetic rule (4) if the agents of the pair have the same opinion, they impose their opinion on their neighbours. However, if the two agents disagree, each agent imposes its opinion on the other agent's neighbours. These rules are shown in Figure 2.

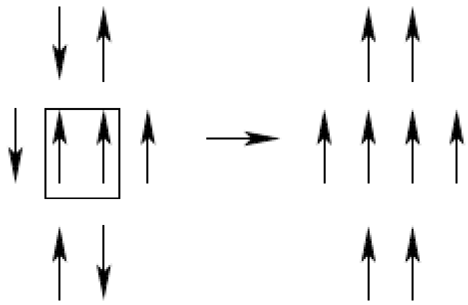


Fig. 2. The principle of Sznajd Model [1]

The antiferromagnetic rule is unrealistic and in the most applications is not used [14]. Only the ferromagnetic rule applies. In this case, if the opinions of the pair of agents differ, they have no influence on their neighbours. There are many extensions of Sznajd model [1]. The Sznajd model has found applications in different areas [14], [15]. In politics, it has been used to describe voting behaviour in elections. It has also adopted to model the competition of different products in open market and the spread of opinions among traders.

Bounded confidence model

The bounded confidence models represent continuous opinion dynamics model [16]. The term of continuous refers to the opinion space and not to the time. Thus, opinions in bounded confidence model are represented by real number in range 0 to 1. The principle of these models is that each agent can interact with each other but true communication between agent takes place only if the opinion of agents involved in discussion is sufficiently close. This realistic aspect of human communications is called bounded confidence and it is expressed by introducing a real number ε into model. The number ε is called uncertainty or tolerance. Therefore each agent with opinion x can interact with other agent whose opinion lies in the interval $[x-\varepsilon, x+\varepsilon]$. The most popular Bounded confidence models are Deffuant model [17] and Hegselmann–Krause model [18]. In Deffuant model two randomly selected agents i and j interact at the time t with opinion $x_i(t), x_j(t)$, respectively. If $|x_i(t) - x_j(t)| < \varepsilon$ then $x_i(t+1) = x_i(t)$, $x_j(t+1) = x_j(t)$. Otherwise, the opinion of interacting agents is adjusted as follows:

$$\begin{aligned} x_i(t+1) &= x_i(t) + \mu[x_j(t) - x_i(t)] \\ x_j(t+1) &= x_j(t) + \mu[x_i(t) - x_j(t)] \end{aligned} \tag{6}$$

Where μ is the convergence parameter taken between 0 and 0,5.The Deffuant model is based on a compromise strategy: the positions of the interacting agents get closer to each other, by the relative amount μ. This model is quite similar to Hegselmann–Krause. The Hegselmann–Krause model is given by:

$$x_i(t+1) = \frac{\sum_{j \in I(i,x(t))} x_j(t)}{|I(i,x(t))|}$$

$$I(i,x(t)) = \left\{ \begin{matrix} 1 \le j \le N| \\ |x_i(t) - x_j(t)| \le \varepsilon_i \end{matrix} \right\}, \quad \varepsilon_i > 0 \tag{7}$$

where:
$x_i(t)$ – an opinion of agent i, $x_i(t) \in \langle 0,1 \rangle$
N – a number of agents
ε_i – a confidence level of agent i
$I(i,x(t))$ – a set of agent identifiers, where for each $j \in I(i,x(t))$, agent j interacts with agent i
The difference is given by the update rule. In Deffuant model agent i interacts with only one of its neighbours, while in Hegselmann–Krause model all its compatible neighbours affected an opinion x_i of agent i. Thus, Deffuant's model is suitable to describe the opinion dynamics of large populations, where people meet in small groups, like pairs. In contrast, Hegselmann–Krause rule is intended to describe formal meetings, where there is an effective interaction involving many people at the same time. More information about bounded confidence models can be found in [1], [19], [20].

Social impact theory

The theory of social impact was introduced in [21] by Latane. The psychological theory of social impact describes how much impact is experienced by individuals. According to the theory, the social impact depends on three factors:
S – the power of persuasion (the strength of source),
I – the immediacy of the sources,
N – the number of sources.
The relation between these factor is usually presented as abstract function $W = f(S, I, N)$ [22]. The factor S describes the ability to persuade another person. The immediacy can be viewed as physical distance between individuals.

Suppose we have a population of *N-agents*. Each agent i is characterized by three factors:
o_i – current opinion supported by agent i,
s_i – agent's ability to convince someone to change or to keep its opinion,
z_i – max. distance within agent's surroundings, in which agent i can communicate with other agents.

The total social impact I_i that an agent i experiences from its social environment is:

$$\mathrm{I_i} = \sqrt{\left(\sum_{j=1}^{N}\left(\frac{s_j}{d_{ij}^2}\right)^2\right)} \tag{8}$$

The factor d_{ij} is the distance of a pair of agents i and j. In original social impact model, agents are represented as cells in the square matrix. It is a form of a regular network. Therefore, the factor d_{ij} in this model is calculated as the Euclidean physical distance between the cells representing two individuals in the matrix. The principle of this model is assumption that agent changes his current opinion to an opinion, which has the greatest support in the agent's environment. This principle is called as conformity. The formal definition of the model is defined in the following way:

$$A = \{a_i = (s_i, z_i, c_i, o_i): s_i \in (0,1),$$
$$z_i \in \mathbb{N}, c_i \in C, o_i \in P, i = 1, \dots, N\}$$
$$|A| = N$$
$$P = \{p_1, \dots, p_K\}, |P| = K$$
$$C = \{(x,y): 1 \le x \le N, 1 \le y \le N, x, y \in \mathbb{N}\}$$
$$d_{ij} = \left\{ \begin{matrix} \|c_i - c_j\|_2 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \, for \; i \ne j \\ 1 \; for \; i = j \end{matrix} \right\}$$
$$w_i = [w_{i1} w_{i2} \dots w_{iK}] \tag{9}$$
$$w_{ik} = \sqrt{\sum_{j=1}^{N}\left[\frac{s_j}{(d_{ij})^2} f(p_k, o_j, d_{ij} - z_i)\right]^2}$$
$$f: PxRxR \to \{0,1\}$$
$$f(p,o,d) = \left\{ \begin{matrix} 1 \; if \; d \le 0 \; and \; p = o \\ 0 \end{matrix} \right\}$$

where:
a_i – an agent i
w_{ik} – a value of support for opinion k for agent i
P – a set of opinions
c_i – a coordinate of agent i in the grid (square matrix)
f – a function that defines a possibility of communication between agents.

The algorithm of changing agents' opinions is given in the following way:

for each agent a_i, i = 1 to N do:

- calculate w_i
- calculate $u = [u_1, \ldots, u_N]$, where
  $u_i = arg \max_{k=1..K} w_{ik}$ (10)
- $o_i := p_{u_i}$ for $i = 1..N$

One of main disadvantage of the social impact model is to ignore some realistic feature of social interaction i.e. the existence of a memory of individuals. The model can be modified to be used to model other processes related to social behaviour [1], [22], [23].

3. Proposed model

The author proposed extended social impact model by introducing the social network [23] as an agent's environment. The social impact model, originally proposed by Latane [21], uses a regular network to describe interactions between agents. It's unrealistic the topology of interactions between people in society. Therefore, networks (regular, random, scale-free, small-world, hierarchical) [6], [25], [27] are applied in the proposed model. The complex network can be represented as directed graph in the following way:

$$G = \langle V, E \rangle \qquad E \subset VxV \tag{11}$$

where:
G – a directed graph
V – a set of nodes
E – a set of edges.

In the network each agent is represented by one node. Introducing network as an agent's environment requires to redefine a way of calculating distance between agents (d_{ij}) in equation (9). The factor d_{ij} is the shortest path length between node v_i and v_j and it is calculated as the minimal number of edges linking nodes v_i and v_j:

$$d_{ij} = min\left[l_1(v_i, v_j), \ldots, l_H(v_i, v_j)\right], \quad l_h : E \to \mathbb{N} \quad i, j \in V \tag{12}$$

where:
d_{ij} – shortest path length between node v_i and v_j
$l_h(v_i, v_j)$ – the number of edges linking nodes v_i and v_j for path h

4. Simulations

The experiments were performed in order to investigate how the distribution of opinion in the population depends on parameter z. The setting of simulation is shown in Table 1. Table 2 presents detailed properties of networks used in experiments.

Tab. 1. The setting simulation – the dependence of parameter d on the distribution of opinion in population

Number of agents		~1000
Number of opinions		2
Network types		Regular Random Scale-free Small-world Hierarchical
Agent types:		Strong agent Common agent
Strong agent	Population:	10% of population
	Power of persuasion (s):	0,8
	Parameter (z):	1…10
	Initial opinion (o):	Opinion 2
	Location in network:	Random
Common agent	Population:	90% of population
	Power of persuasion (s):	0,2
	Parameter (z):	1…10
	Initial opinion (o):	Opinion 1
	Location in network:	Random

Tab. 2. The properties of networks used in experiments

Property	Network				
	regular network	scale-free network	hierarchical network	small-world network	random network
The number of nodes	900	1000	1025	1024	1000
The number of edges	1740	999	1024	4992	1000
Average degree	1,933	1,998	0,999	4,875	1
Network diameter	99	18	9	9	7
Graph density	0,002	0,002	0,001	0,005	0,001

Additionally, the Figure 3 shows networks used in experiments.

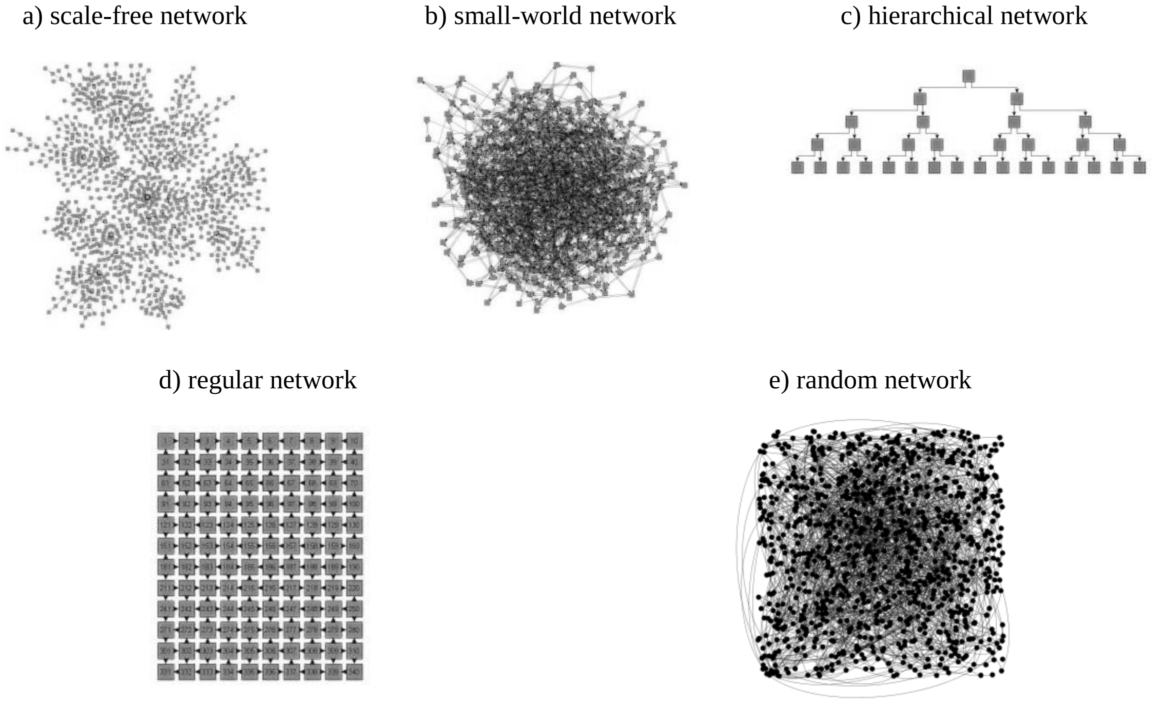


Fig. 3. Types of networks used in experiments

Generally, five kind of complex networks were used. For each of these networks, the impact parameter *z* on the distribution of opinion was observed. The parameter *z* changed from 1 to 10. The author assumed that all agents had the same value of parameter *z*. The simulation results are presented in Table 3. All values are averaged over 30 runs.

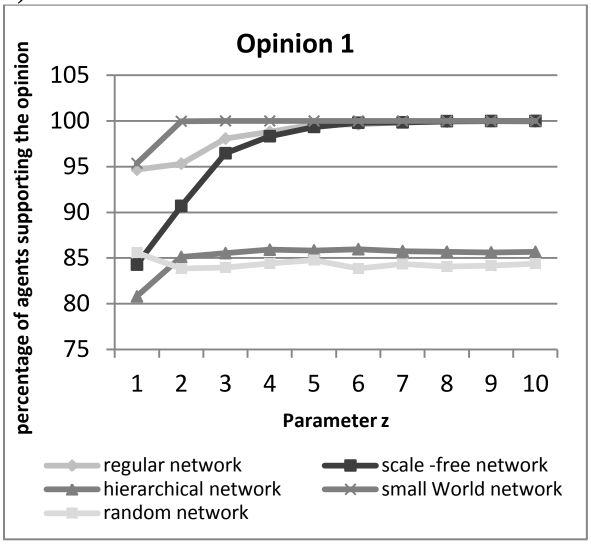
Tab. 3. The simulation results

Network	z									
	1		2		3		4		5	
	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]
regular network	94,67	5,33	95,33	4,67	98,07	1,93	98,81	1,19	99,63	0,37
scale-free network	84,28	15,72	90,71	9,29	96,47	3,53	98,33	1,67	99,35	0,65
hierarchical network	80,80	19,20	85,13	14,87	85,54	14,46	85,91	14,09	85,84	14,16
small-world	95,36	4,64	99,96	0,04	100,00	0,00	100,00	0,00	100,00	0,00
random network	85,58	14,42	83,85	16,15	83,98	16,02	84,41	15,59	84,78	15,22

Network	z									
	6		7		8		9		10	
	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]	Opinion 1 [%]	Opinion 2 [%]
regular network	99,62	0,38	99,87	0,13	99,89	0,11	99,96	0,04	99,93	0,07
scale-free network	99,80	0,20	99,85	0,15	99,98	0,02	99,99	0,01	100,00	0,00
hierarchical network	85,97	14,03	85,76	14,24	85,69	14,31	85,62	14,38	85,68	14,32
small-world	100,00	0,00	100,00	0,00	100,00	0,00	100,00	0,00	100,00	0,00
random network	83,85	16,15	84,36	15,64	84,08	15,92	84,16	15,84	84,39	15,61

The Figure 4 shows the percentage of agents supporting opinion 1 (a) or opinion 2 (b) in population for different value of parameter z.

a)



b)

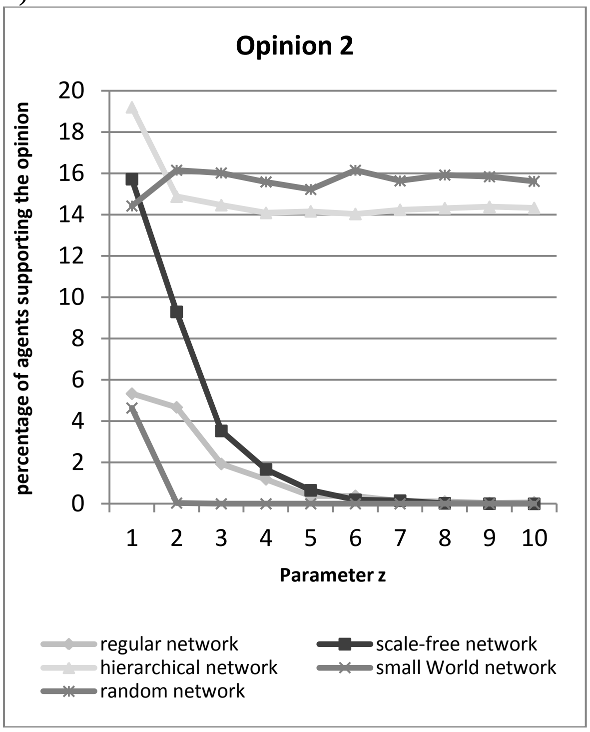


Fig. 4. The graph of agents supporting opinion 1 (a) and opinion 2 (b) in population for different value of parameter z

Based on simulation result, there is no correlation between z and distribution of opinions for random network and hierarchical network. In these networks, the increasing value of z has insignificant impact on the final distribution on opinion. For other network there is a relation between the value of z and the distribution of opinion. The experiment showed that small-world network is very sensitive for changing value of z. For $z = 2$ there is only one opinion, which is supported by entire population. The minority *opinion 2* was complete disappeared. In the case of scale-free network and regular network this phenomenon (disappearance of minority opinion) occurs for $z > 6$. The explanation of this phenomenon is not intricate. It was mentioned early that the principle of social impact model is based on conformity. Additionally, the parameter z is responsible for scope of agent's information about other agents' opinions. Given these two factors we receive explanation of experiment results. If agents have high value of z and they change their opinion according to the conformity rule, it is expected that minority opinion will be complete dominated by majority opinion in the population. Thus, an opinion supported by small group will be disappeared from population. The experiment results for hierarchical network and random network are different from other, because these networks have specific structure, where increasing value of z doesn't cause that the agents have more information about opinions in the population. In these network we observed that the set of agents' neighbours for each agent is small and limited. The findings of this experiment reveal disadvantage of social impact model. There is no way to model behaviour based on non-conformity rule using this model. In real community there are individuals that have a little (or no) ability to persuade others but on the other hand, it's hard to convince them to change their opinions. This drawback limits the application of the social impact model.

The complex network has many interesting properties but one of them is very interesting especially in connection with a problem of distribution of opinion. In these networks we could find some special nodes, which have high value of centrality. Many types of measures of centrality could be identified [28], [29], [35], but three measures were chosen, which were used in experiment:

a) degree centrality [28] – it is defined as the number of adjacent edges of node (the degree of a node):

$$C_{degree}(v_i) = k_i \tag{13}$$

where:

k_i – a number of edges connected to node v_i

The degree centrality measure, defined according to equation (13), does not allow for centrality values to be compared across different networks. It should be normalized in the following way:

$$C_{degree}^{norm}(v_i) = \frac{k_i}{n-1} \quad (14)$$

where:
n – a number of nodes in network,
k_i – a number of edges connected to node v_i.
In directed networks, there are two types of degree centrality: in-degree and out--degree [29];

b) closeness centrality [28], [29], [35] – it is defined as:

$$C_{closeness}(v_i) = \frac{1}{\overline{d_{v_i}}}$$
$$\overline{d_{v_i}} = \frac{1}{n-1}\sum_{j \in V/\{v_i\}} d_{ij} \quad (15)$$

where:
n – a number of nodes in network,
d_{ij} – the shortest path length between node v_i and node v_j (the geodesic path),
$\overline{d_{v_i}}$ – the average shortest path length between node v_i to other nodes;

c) radius centrality [30], [35] – it is defined in the following way:

$$C_{radius}(v_i) = \frac{1}{\max_{j \in V} d_{ij}} \quad (16)$$

where:
d_{ij} – the shortest path length between node v_i and node v_j.

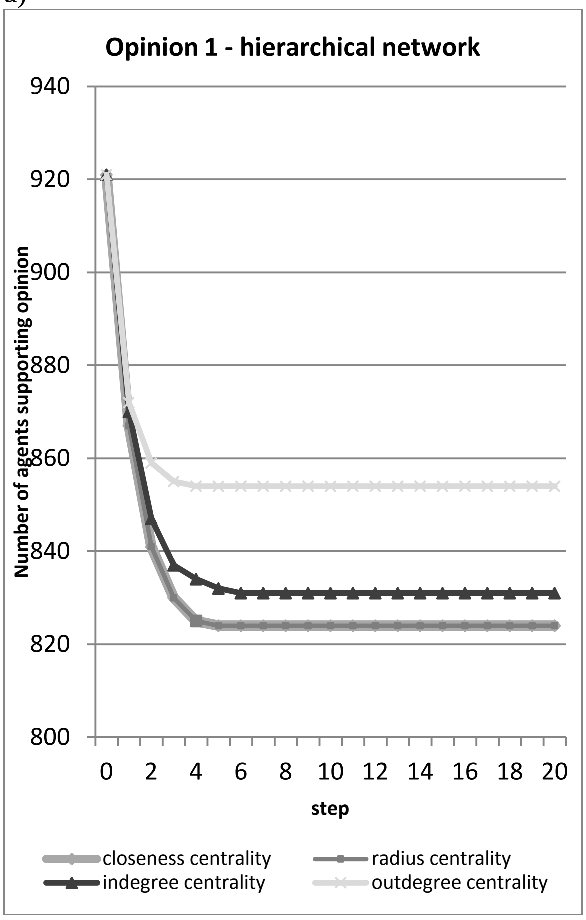
The measure of centrality is node property. A node which has high value of centrality measure is called hub. It means that this node plays an important role in the network and should have an impact on distribution of opinion in network. Therefore, some experiments were conducted with different scenarios in order to determinate the dependence of the position of the agent on the distribution of opinion in the population. According to the power of persuasion, two types of agents are identified: "strong agent" and "common agent". At the beginning of all simulations, strong agents supported opinion two and common agents supported opinion one. It was an assumption that the space of opinions is limited to only two opinions and the number of strong agents was 10% of all agents. The agents were located in nodes depending on the power of persuasion (s) and the value of centrality (C). The agent with high value of s was located on node with high value of centrality. The detailed setting of simulation for these experiments is shown in Table 4.

Tab. 4. The setting of simulation – centrality measure experiment

Number of agents	~1000
Number of opinions	2
Network types	Regular Random Scale-free Small-world Hierarchical
Agent types:	Strong agent Common agent
Strong agent	Population: 10% of population Power of persuasion (s): 0,8 Parameter z: 1 Initial opinion (o): Opinion 2
Common agent	Population: 90% of population Power of persuasion (s): 0,2 Parameter z: 1 Initial opinion (o): Opinion 1

The simulation results are shown on Figure 5. The Figure 5 a, b, c, d, e shows the distribution of opinion for each type of centrality measures and each type of network.

a)



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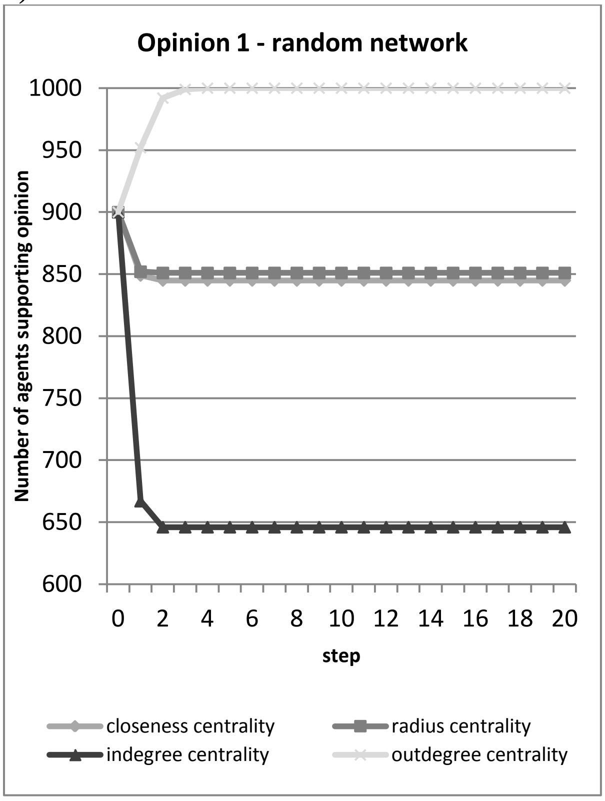

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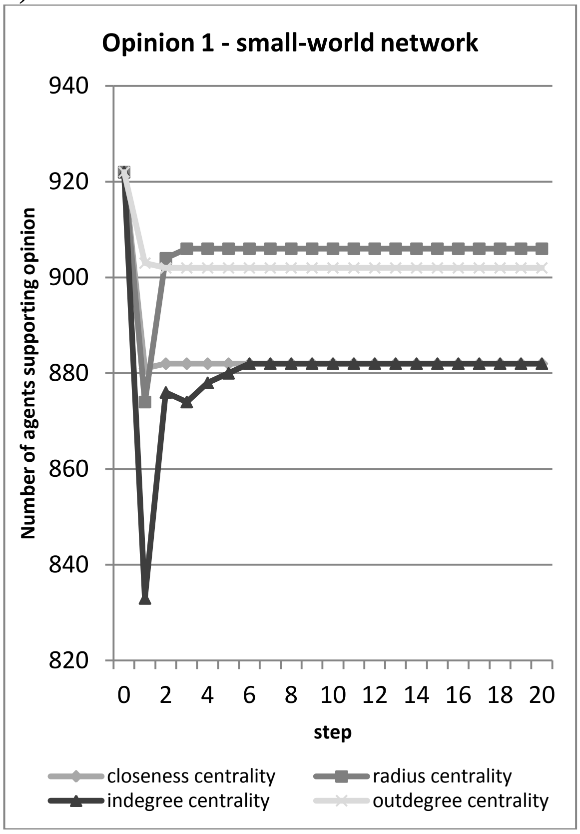

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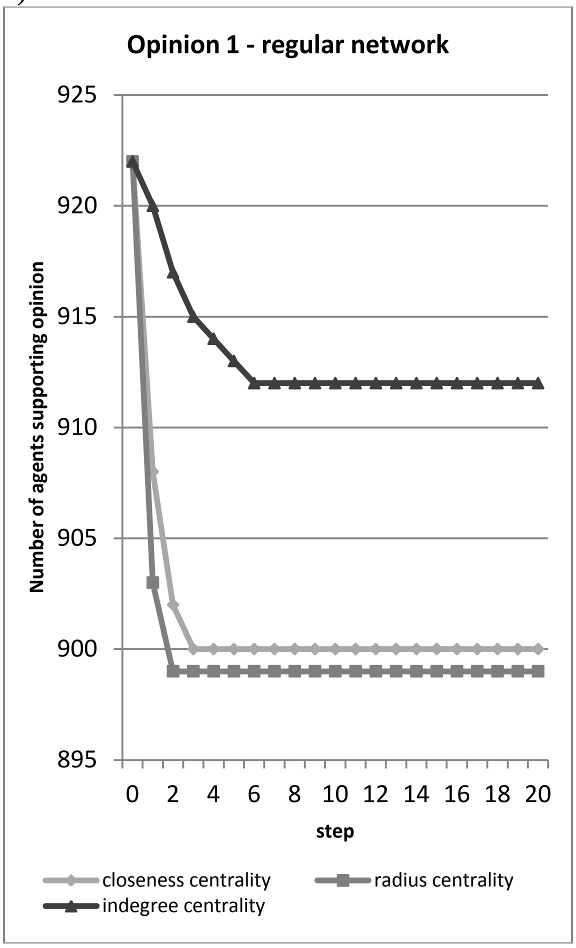

e)

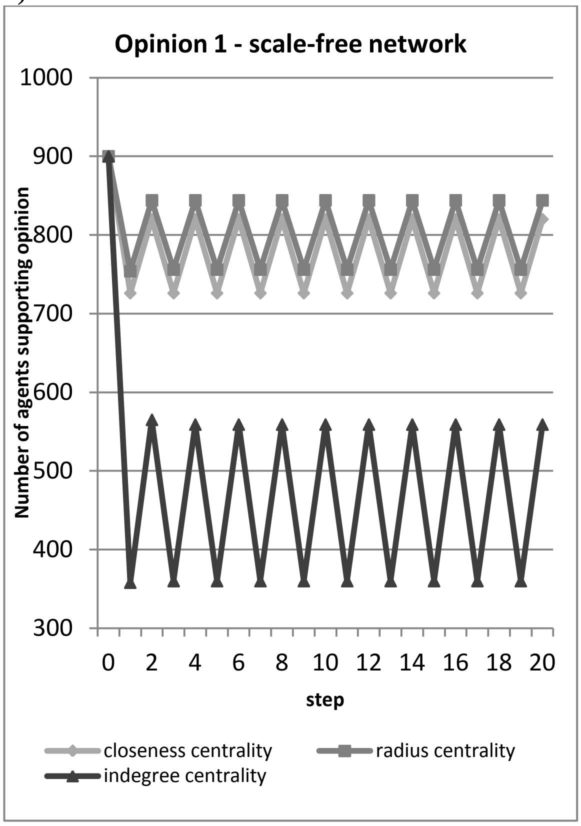

Fig. 5 a, b, c, d, e. The distribution of opinion 1 for different type of complex network and the way of agent location

One can notice that the final support for *opinion 2* is much higher than at the start of simulation for the most cases. It confirms that locating strong agents in nodes with high value of centrality has significant impact on the distribution of opinion in the population. It also indicates that the support for opinion depends on: the topology of interaction between agents (which is related to the type of network) and the way of locating agents. The following conclusions could be drawn:

a) The location of strong agents in nodes with high value of degree centrality has the greatest impact on the distribution of opinion in scale-free network and small-world network. There is no significant different between radius centrality and closeness centrality for all networks expect small-world network. Only for small-world, it could be noticed different between radius and closeness centrality. The radius centrality has less influence on the distribution of opinions for these network.

b) The nodes with high value of radius centrality or closeness centrality play a key role in the distribution of opinions in hierarchical network. Based on results, the number of agents supporting *opinion 2* is the biggest for radius centrality and closeness centrality. Similar result was obtained for regular network. Additionally, this result is opposite to result for scale-free network and small-world network.

The experiment provided some interesting results for random network. The most of results obtained for this network are similar to results for other networks. One exception is result for out-degree centrality. This configuration caused that *opinion 2* is complete dominated by *opinion 1* and entire population finally supports *opinion 1*. The most likely reasons are: the network structure and the properties of social impact model.

5. Conclusion

In this paper, the author have presented the social impact model with the complex network as the topology of interaction between agents. The author have studied the use of different complex networks in the social impact model. The results have confirmed that the topology of interaction between agents have significant impact on the process of spreading opinions Many experiments were performed to evaluate the impact agent's parameter *z* and the way of agent location in network on the distribution of opinions. The results of experiments, involved with the location of agents, showed that the agents' location has highly influence on the final distribution of opinions in the population. It should be considered as a key element of models of opinion dynamics. There are several problem required further research. One of them is a problem with the location of agents. It's an open question what decide that a specific agent is located in the hubs. In this paper, the power of persuasion (the feature of agent) was chosen but this problem requires further detailed research.

The results also indicate that the effect of consensus occurs more frequently, when individuals have more information about the distribution of opinions in the population. It is caused by the basic principle of social impact model – conformity.

In presented studies each agent communicated with all his neighbour's agents in each simulate step. Interesting topic would be to introduce a probability of communication between agents. Another interesting work would be to study the effect agent's memory on spreading opinions.

The experiments confirmed that the social impact model is inadequate to model real individual behaviour. Thus, the future work will focus on an extension of model by adding additional agent features that will be able to model complex agent behaviours, especially non-conformity behaviours.

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Zastosowanie sieci złożonych w modelu wpływu społecznego

D. DZIDA

W artykule przedstawiono zagadnienia związane z modelowaniem dynamicznych modeli opinii. Zaprezentowano różne koncepcje dotyczące sposobu modelowania rozpowszechniania opinii w społeczeństwie. Zaproponowano modyfikację modelu opinii bazującego na teorii wpływu społecznego poprzez wprowadzenie sieci złożonych. Zbadano wpływ rozmieszczenia jednostek na ostateczny rozkład opinii dla różnych typów sieci złożonej. Dokonano również analizy wpływu wartości maksymalnego współczynnika odległości jednostek na końcowy rozkład opinii w społeczeństwie.

Słowa kluczowe: model opinii, model wpływu społecznego, sieci złożone.