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Chapter

Modelling the Information-Psychological Impact in Social Networks

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Abstract

The paper considers the objects, subjects, purposes, tools, methods and implementation of information-psychological impact (IPI). It suggests a cellular automata model of the diffusion process of information-psychological impact in social networks, the hierarchy of the changes in the states of the subjects of information-psychological impact and the chart of transitions from state to state used in the cellular automaton algorithm. The suggested cellular automaton takes into account the effect of forgetting the information-psychological impact, as well as social and psychological parameters and probabilistic characteristics of the subjects of the social network. It therefore allows for the modelling of the diffusion of the information-psychological impact in the social network. The model can be used to determine the number of subjects affected by the information-psychological impact and the possibility of successful diffusion of the impact. The modelling of the suggested algorithm was performed. The results of the modelling are analysed in the paper.

Keywords: social network, information-psychological impact,
negative information-psychological impact, positive information-psychological impact, cellular automata, diffusion, social and psychological parameters

1. Introduction

Information-psychological impact (IPI) is the informational influence on people's minds, which alters their perception of the reality, behavioural functions and, in some cases, even the functioning of their inner organs and body systems [1–3]. Information-psychological impact (IPI) may affect individuals, groups of people, communities and the whole society. IPI can be either positive or negative, depending on the intended purpose. Positive IPI is used for medical treatment purposes, rehabilitation, improvement of behavioural patterns and creative purposes. It can also be used to unite people for a good cause. Negative IPI is used for manipulating—directly or indirectly—individuals, groups of people or the whole society into actions that violate either their own interests or interests of others. Negative IPI may cause emotional, psychological and social tensions, deterioration of moral standards and behavioural norms, as well as moral and political disorientation. This, in turn, leads to dramatic changes in individual, group and public

conscience and alterations in the moral, political, social and psychological environment within the society [1–3].

Information-psychological impact is implemented by means of various tools and techniques. At the moment, negative information-psychological impacts are more common. They influence individuals, groups of people or the society by means of telecommunication systems, mass media and social networks. Negative IPIs are used to control the society, force certain opinions on various issues, recruit members to religious cults and terrorist groups and to alter people's mental state. Among the examples of such IPIs are colour revolutions, the so-called "death groups" on social networking sites, as well as active recruitment campaigns to terrorist groups, which are based on films or video games aimed primarily at young people.

It is thus very important to model IPIs in social networks in order to analyse and select the most effective methods of using positive IPIs and combating negative IPIs [1, 2, 4].

2. Overview of previous studies

Social networks are usually represented as graphs with multiple vertices (agents) and edges representing the links between the agents. Agents represent various subjects of the network, from individuals to large groups, organisations and communities. Links denote the relationships between the agents, such as information exchange, social relations and communication [4–9]. The process of IPI can be divided into two stages: diffusion of the IPI and alteration of the agents' opinions. Gubanov et al. [4] consider various models of social networks and divide the tasks connected with studying IPI into following groups: modelling of the informational influence, modelling of the information management and modelling of the information confrontation.

Models of the informational influence are used to study the behaviour of the subject affected by IPI. The influence may be intentional or unintentional. Social influence becomes obvious during communication or in case of comparison. Models of the informational influence are used for information management, as they help the managing subject to determine the kind of informational influence that will make the controlled subject behave in the desired way. The information management model, in turn, is used to model information confrontation, that is, the interaction of several subjects with conflicting interests who apply their informational influence to the same controlled subject [4]. There are a number of approaches to modelling the influence.

1. The Independent Cascade and Linear Threshold Models [4, 8, 10–13]. In these models, the subject (a vertice of the graph) can be either active or inactive. The state may only change from active to inactive, not the other way round. The agent becomes active depending on the selected threshold. The threshold can be uniform for all agents or may be randomly selected according to a probabilistic distribution. These models do not take into account groups, game interaction between the subjects, individual activity of the subjects or incomplete awareness of the subjects.

2. Network autocorrelation models. In these models, the opinion and behaviour of the subject are affected by the opinion of the neighbouring subjects and represent the reaction of the subject to the IPI. The authors [14–19] consider a determined time-digital linear process, where opinions (properties) of the

subject are presented as vector y_t and change under the influence of other subjects according to the so-called influence matrix W: $y_{t+1} = Wy_t$.

3. Ising models [20, 21]. Invented for studying the phenomenon of ferromagnetism, Ising model is often used to verify the results of numerical modelling. When studying the diffusion of IPI in social networks, the model helps to describe the changes in the behaviour of a large social group caused by the nearest neighbours. The influence of the nearest neighbours plays a key role, and the willingness of the group to accept a new idea serves as the analogue of the temperature.

4. Influence models based on Markov chains. Such models employ corresponding mathematical tools to represent the activities of every subject and the group as a whole. They are used to analyse social dynamics and determine the patterns of the group behaviour. The authors [22–24] consider the similarity of opinions of the subject, the authors [7, 24] focus on the time over which the opinions become similar, and the authors [7, 25] study the conditions under which a uniform final opinion is formed.

All the above-mentioned models represent the rules of interaction between the subjects or groups of subjects. However, they either do not at all represent the specifics and characteristics of the network influence and the interaction process or do this inadequately.

When a social network is considered as a set of agents [4, 26–28], we assume that every agent has a certain degree of influence on the other agents. It is therefore necessary to determine a small group of agents with the maximal level of influence, that is, to solve the influence maximisation problem [4, 10, 29]. These agents can be used as key nods for influencing other subjects of the social network or to monitor the social network in order to reveal the presence of IPI. The influence maximisation problem has been considered in papers focusing on the following issues.

- Viral marketing [29], where a social network is represented by a Markov chain with each agent A having his own value that depends on the profit from sales to other agents influenced by agent A.

- Influence maximisation in the models of innovations' diffusion [10]. They include a set of active agents, and at a certain point in time, a new active agent can activate his neighbours with a set probability.

- Voting process modelling [9], where every agent can, at any stage, change his opinion by accidentally voting for one of his neighbours and adapting their opinion. The agent is more likely to adapt the opinion supported by the majority of his neighbours.

Besides analysing the influence, management and confrontation, there is also a problem of diffusion of information-psychological impact in the information space [5]. Information may spread in the following directions [5, 30]: from a subject to another subject, from a subject to a group, from the information production centre to an individual subject or a group.

The authors [5, 26–28, 31] suggest a multi-agent model of information diffusion. The model takes into account the growth of the number of agents over time. Agents

may appear themselves, produce new agents, disappear from the subjects' neighbourhood or receive links from other agents.

In [5, 30], the life cycle of the information flow is represented by information diffusion models based on cellular automata. In these models, each cell of the automaton can have various states, such as "influence taken," "influence not relevant," or "influence rejected." The information spreads according to probabilistic rules. The observed states of the objects alter simultaneously in discrete time intervals following the constant local probabilistic rules. The rules themselves depend on the state of variables describing the nearest neighbours of the agent or on the state of the subject itself. For instance, the authors [8, 32] present a model of word-of-mouth information transfer considering strong and weak links between the subjects.

In order to analyse the information diffusion process, the authors [6, 33, 34] compare information diffusion to virus transmission using infiltration and contamination models such as SIR model and SIRS model.

Runkov [35] compares the structure of social networks and neural networks. Individual users are viewed as neurons. Using the information about the users' activities, the neural network may forecast the kind of news they will be interested in [35, 36] also suggests using neural networks to forecast the behaviour of the subject of IPI and their recruitability to certain assignments, as well as to assess their reliability using the data available in the social network.

From the information security perspective, it is vital to identify IPI as soon as possible. For this purpose, the authors [4, 37] suggest monitoring the states of a small group of nods in the network using graph models. The problem is to determine the set of nods to be monitored. Deviations from the standard dynamics of transmission of some information messages may serve as an indicator of information-psychological impact. In order to analyse the dynamics of the information spread and determine the channels caused by external factors, wavelet analysis can be used [5, 15, 17].

Dodonov and Lande [5] introduce the term information reservation for an isolated area of the information space and suggest certain modification to information diffusion models in order to model the dynamics of information flows in information reservations. Information reservations are information areas subject to constant information-psychological impact. They can be used for information and psychological control over the society.

We should say, however, that all the suggested models do not fully consider social and psychological factors, such as the psychological state of the subjects during IPI diffusion in social networks. IPI diffusion process depends on the probabilistic characteristics of the subjects of the social network and the links between them. It is, therefore, interesting to study IPI diffusion taking into account social and psychological factors and the psychological state of the subjects of the social network.

The aim of this paper is to model the process of IPI diffusion in social networks considering social and psychological factors and the psychological state of the subjects of the social network. This can be done using a cellular automaton model, as cellular automata can most adequately represent the process of IPI diffusion in a social network and the changes in the opinions of its subjects caused by their immediate neighbours, taking into account social and psychological factors.

3. Materials and methods

When modelling and analysing the process of IPI diffusion, we regarded the social network as a two-dimensional cellular automaton. A two-dimensional cellular

automaton is a set of finite automata (subjects of the social network) allocated on the reference frame and marked with integer coordinates (i,j). Each automaton can have certain properties and be in one of the states $S_{i,j} \in \{S_1, S_2, .., S_k\}$. The state of a finite automaton (i,j) at a certain moment in time $t+1$ is determined as follows Eq. (1):

$$S_{i,j}(t+1) = F(S_{i,j}(t), N(i,j), t), \qquad (1)$$

where F is the rule for the transition of state of the automaton; $N(i,j)$ is the point neighbourhood (i,j) and t is a step on the axis of time.

In the cellular automaton model, each cell changes its state while interacting with a limited number of other cells, normally adjacent ones with the same edge or vertex. Such models allow for a simultaneous change of the state of all cells following the general principle of the cellular automaton. Therefore, it is easy to see the connection between the processes occurring on the micro level and the processes of spatial interaction between the elements.

Due to the simplicity of their implementation and the ability to describe complex processes, cellular automata are widely used for the modelling of systems, which consist of a large number of nonlineary interacting particles (fluid and gas dynamics in various environments, fires, traffic, and so on), as well as for representing collective phenomena, such as turbulence, arrangement and chaos.

3.1 Suggested models of IPI in social networks

Given below are the models we suggest for describing the process of information-psychological impact diffusion in social networks.

1. Information interaction within the social network is presented as a two-dimensional cellular automaton, whose grid is a two-dimensional array, where each cell is numbered with an ordered pair (i,j). Each cell is a subject of the social network. The nearest neighbours of each cell are considered the cells that have a common vertex with the one observed (Moore neighbourhood). Thus, each cell has eight nearest neighbours. To eliminate the tip effect, the grid of the cellular automaton is topologically twisted into a torus [5, 30, 38], that is, the first line is considered to be the continuation of the last one, and the last one precedes the first one. The same applies to the columns [5, 30, 38–40].

2. The informational interaction in the social network is presented as a cellular automaton, whose grid is a free-scale network generated by a Barabási-Albert algorithm.

Each cell may be in one of the following states: highly positive, neutral (mild negative or positive attitude) or highly negative. Depending on its state and social and psychological characteristics, a cell may or may not spread the information (by influencing the neighbouring cells) [5, 30, 38]. The state and behaviour of cells change according to the set of rules for the suggested model. These rules take into account social and psychological factors as well as the psychological state of the subjects of the social network.

A state transition graph is presented in **Figure 1**. S_0 is the initial state; S_1 is the subject that does not spread the information I and his negative opinion (negative feedback); S_2 is the subject that does not spread the information I and his positive opinion (positive feedback); S_3 is the subject that spreads the information I together
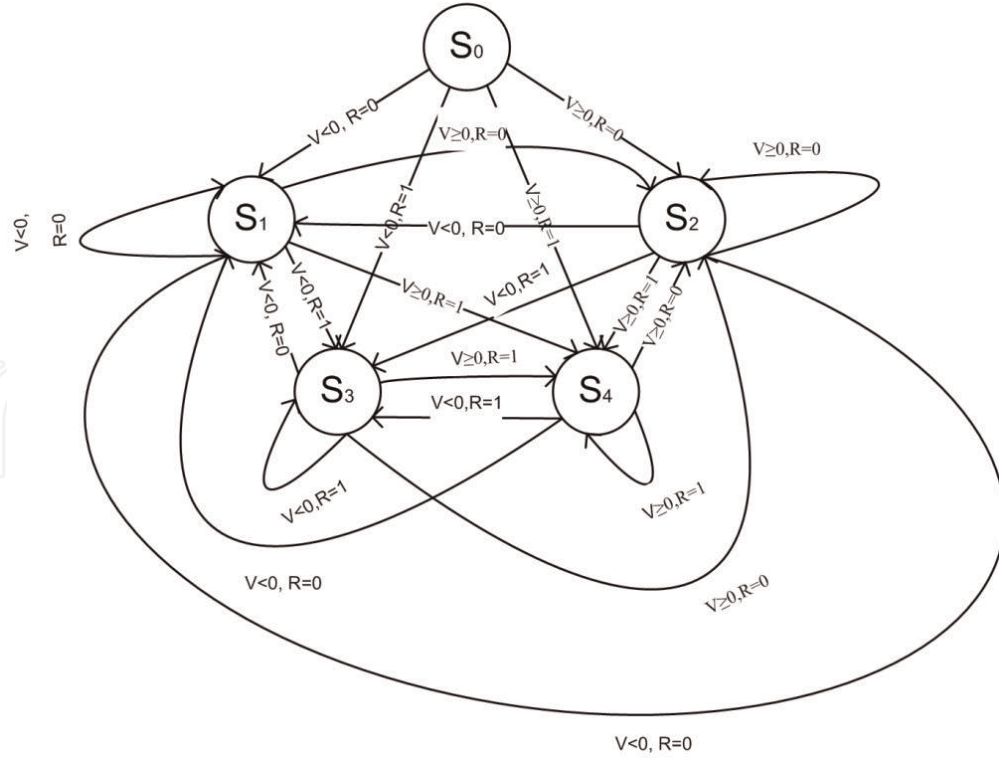
Figure 1.
State transition graph.

with his negative opinion (negative feedback); S_4 is the subject that spreads the information I together with his positive opinion (positive feedback).

Each subject P_k of the social network is interested in a certain number of topics $T^k = \{T^k_m\}$ and is indifferent to other topics. Subject P_k has the following social and psychological parameters [41].

1. Initial personal opinion V_k about the information presented in the IPI, which depends on individual psychological characteristics, education, moral principles, environment and so on. This parameter is evaluated by the experts using Harrington scale, according to which values V_k can be interpreted as follows [41]:

   - $[-1; -0.64)$ interval—highly negative opinion that motivates the subject to spread the information I together with the negative opinion (negative feedback);

   - $[-0.64; 0)$ interval—mild negative opinion that does not motivate the subject to spread the information I;

   - $[0; 0.64)$ interval—mild positive opinion that does not motivate the subject to spread the information I;

   - $[0.64; 1)$ interval—highly positive opinion that motivates the subject to spread the information I together with the positive opinion (positive feedback).

2. Level of trust $TR_{kj}{}^{T_I}$ to the j-th user concerning the topic T. This parameter influences the attitude of subject P_k to the information presented in the IPI,

received from j-th source. The set of $TR_{kj}{}^T$ forms a "trust matrix" TR^{T_I} for the topic T_I. The TRTI matrix should not necessarily be symmetric.

3. Communication skills O_k. This parameter is evaluated using various psychological tests, such as Ryakhovsky's test for communication skills. Let O_k = {Bad; Average; Good} [41, 42].

4. Information transfer coefficient G_k, showing the force of influence transmitted by subject P_k to the neighbouring subjects.

5. Level of perception C_k, showing how much subject P_k relies on his own opinion within the topic T_I.

In order to evaluate the current (at a specific time interval $t = t + 1$) opinion V_k^{t+1} about the information presented in the IPI, the following relations are suggested [41]:

$$
V_k^{t+1} = \begin{cases} 1, \ whenever \ X \geq 1, \\ X, \quad whenever -1 < X < 1, \ X = V_k^t + C_k^{T_I} \cdot CSP_k^{t+1} \\ -1, whenever \ X \leq -1, \end{cases} \tag{2}
$$

$$
CSP_k^{t+1} = \frac{\sum_{i=1}^{N} F_i TR_{ki}^{TI}}{N}, \quad F_i = G_i V_i^t,
$$

where CSP_k^{t+1} is an "integral social force," denoting the degree of influence on the opinion of subject P_k about the information in the IPI received from the subject P_k is interacting with; N is the number of subjects interacting with subject P_k; F_i is the force of IPI with which the i-th subject influences subject P_k and V_i^t is the opinion of the i-th subject.

Whether subject P_k will spread the IPI with the force F depends on his opinion V_k and his communication skills O_k. To evaluate the coefficient of the information transfer by subject P_k at a specific time interval $(t + 1)$, the following formula is used [41]:

$$
R_k^{t+1} = \begin{cases} 0, \ if \ O_k = "bad" \text{и} \ V_k \in [-0,64; 0,64); \\ 1, else. \end{cases} \tag{3}
$$

The subject affected by the IPI in the social network develops his own opinion about the received information, which depends on his individual parameters and the force of the IPI. The opinion can be positive or negative and may change over time under the influence of other factors. Depending on his opinion about the information and his communication skills, the subject may or may not spread the received IPI [43–46].

The effectiveness of the IPI can be defined by the following relation Eq. (4):

$$
P = \frac{N_{S_2} + N_{S_4}}{N}, \tag{4}
$$

where N_{S_2} is the number of subjects in state S_2, N_{S_4} is the number of subjects in state S_4 and N is the total number of subjects.

Users of the social network may be subject to various kinds of IPI aimed at different groups of people. IPIs may also differ by their purpose and the effectiveness of implementation. IPI in social networks may also be used to influence specific public officers.

Using the results of the IPI modelling, we can perform a comprehensive assessment of the general level of information and psychological security and suggest practical recommendations on how to eliminate the negative effect of the information-psychological influence. The assessment can be based on the methodology for calculating the security indices in the military, political, economic and other spheres developed by the PIR Center [48, 49]. This means that the index of general information and psychological security (IGIPS) is calculated according to the following formula:

$$
\begin{aligned}
IIPS = \frac{G_0}{H} & \left[f_1(1-\beta_1) + f_2(1-\beta_2) + \dots + f_H(1-\beta_H) \right] + \\
& + \frac{G_{tar}}{K} \left[h_1(1-\gamma_1) + h_2(1-\gamma_2) + \dots + h_K(1-\gamma_K) \right] \chi_i,
\end{aligned}
\tag{5}
$$

where G_o is the coefficient of the degree of IPI on the social network; H is the number of IPIs; f_i is the coefficient of the importance of the i-th IPI; β_i is the probability of using the i-th IPI in the social network determined by the Eq. (4); G_{tar} is the coefficient of the degree of the IPI on the specific management system; K is the number of public officers that may be subject to the IPI; h_i is the coefficient of the importance of the i-th; γ_i is the probability of effective implementation of the IPI used to influence the i-th public officer and χ_i is the coefficient of importance of the i-th management object.

G_o, G_{tar}, f_i, h_i and χ_i are determined by means of an expert survey. The probability of effective implementation of the IPI γ_i used to influence the i-th public officer is calculated using Eq. (6):

$$
\gamma_i = \frac{S}{D},
\tag{6}
$$

where S is the number of wrong decisions made and D is the total number of decisions made after the IPI.

The probability of the IPI being aimed at a specific public officer is calculated using Eq. (7) [2]:

$$
P = 1 - (1-a_i)(1-b_j)\dots(g_s),
\tag{7}
$$

where $a_i, b_j, \dots, g_s$ are informational factors determined by the expert survey that indicate that the IPI is aimed at a certain public officer.

The suggested method of assessing the IGIPS has the following advantages. It registers the increase in the degree of the IPI on the social network in good time. It registers the connection between the IPI on public officials and the decisions they make. It allows for calculating the index of information and psychological security and developing a strategy to decrease negative IPIs.

3.2 Modelling algorithm

Figure 2 presents a flow chart of the algorithm for modelling IPI. During the initial stage, main parameters of the social network's subjects are determined. The trust matrix is formed, and the communication skills of the subjects, their
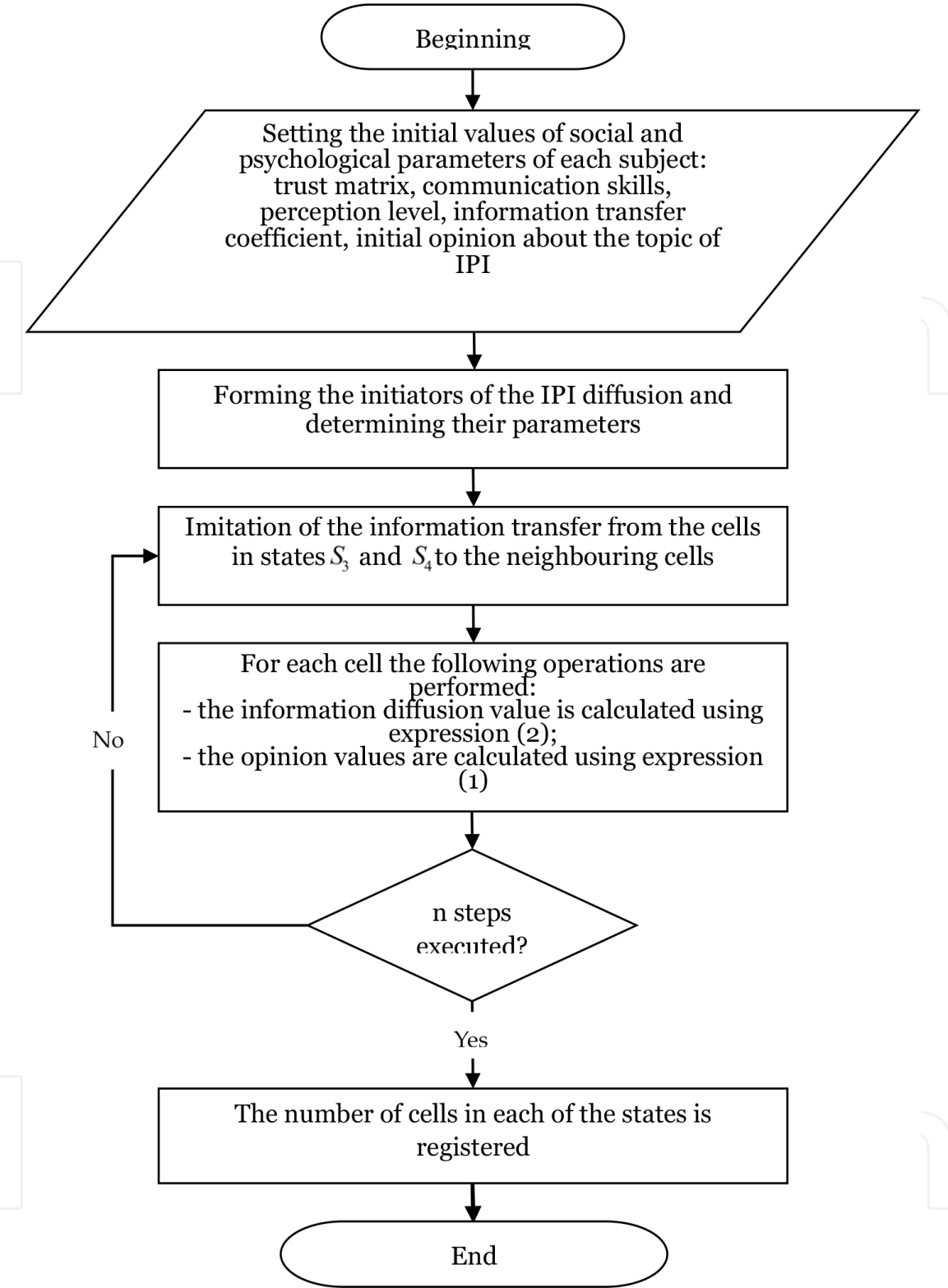
Figure 2.
Flow chart of the algorithm for modelling IPI.

perception level, information transfer coefficient and the initial opinion about the given issue are determined [43–47].

During the first stage, which corresponds to the origin on the time axis ($t = 0$), the whole grid consists of cells in state S_0, except for certain cells that initiate the diffusion of the IPI together with their positive opinion about the information.

The second stage involves information diffusion and exchange of opinions between the subjects along the time axis $t = t + 1$. The information diffusion is calculated using Eq. (3), and the opinions are calculated using Eq. (2). Cells with

the value of information diffusion equal 1 spread the information to the neighbouring cells.

A cell may change its state receiving influence F_i from the neighbouring cells whose information transfer value equals 1. When the influence is received, the current values of opinion V_k and information diffusion R_k are calculated.

4. Experiments and discussion

4.1 Two-dimensional array implementation

The suggested algorithm was implemented on a 100×100 grid. The automaton was tested in the following way: the initial values were distributed following the normal distribution law; 10 random initiators of the IPI and 2 opponents were selected out of all the subjects; the automaton was tested 100 times, each test run including 1000 steps; average number of subjects in each of the states was determined. The initial personal opinion of subject V_k about the information was distributed according to the normal distribution rule within the intervals $[-1; -0.5]$, $[-0.5; 0.5]$, $[0.5; 1]$. Trust level $TR_{kj}{}^{TI}$ was distributed according to the normal distribution rule within the interval $[0; 1]$ or $[-1; 1]$. **Figures 3–5** demonstrate the functioning of the automaton.

Figure 4 demonstrates the functioning of the automaton, when $V_k \in [-0,5; 0,5]$, that is, most subjects are neutral to the IPI. **Figure 5** demonstrates the functioning of the automaton, when $V_k \in [-1; -0,5]$, that is, most subjects are negative to the IPI. **Figure 6** demonstrates the functioning of the automaton, when $V_k \in [0,5; 1]$, that is, most subjects are positive to the IPI. Figures "a" demonstrate the functioning of the automaton, when $TR_{kj}{}^{TI} \in [0; 1]$, that is, the subjects adopt opinions of other subjects. Figures "b" demonstrate the functioning of the automaton, when $TR_{kj}{}^{TI} \in [-1; 1]$, that is, the subject has the opposite opinion to the one imposed by the IPI.
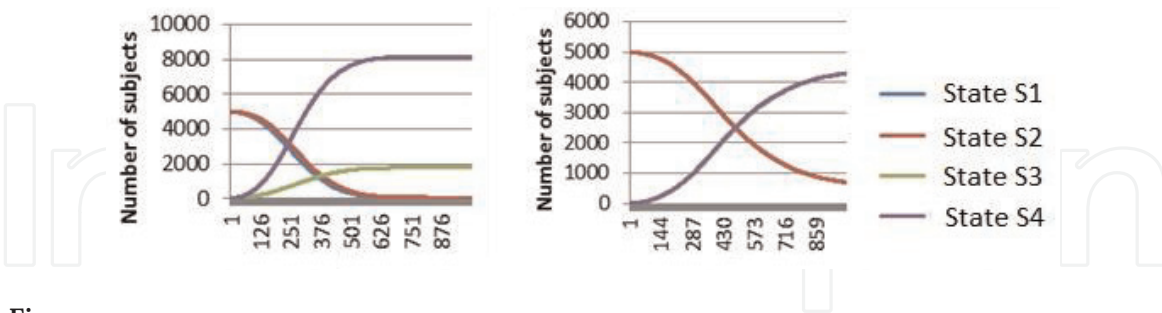

Figure 3.
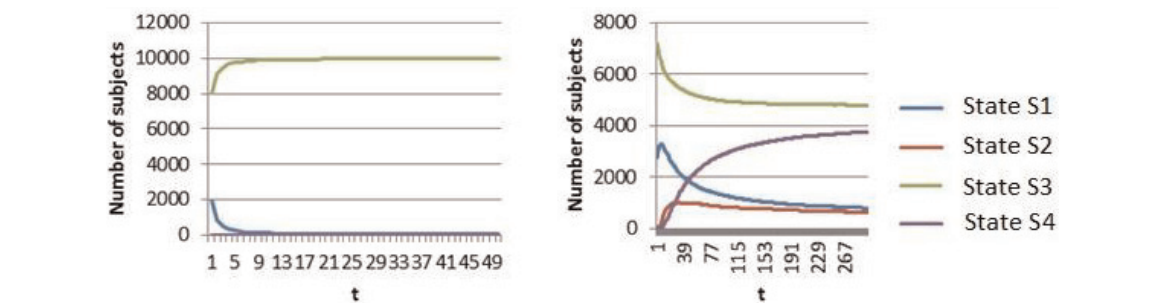*Distribution of cells according to the discrete time whenever $V_k \in [-0,5; 0,5]$.*

Figure 4.
Distribution of cells according to the discrete time whenever $V_k \in [-1; -0,5]$.

4.2 Barabási-Albert model implementation

The suggested algorithm was implemented using a random scale-free network generated by Barabási-Albert algorithm. The network consisted of 1000 nods. The results are given in **Figure 6**. The automaton was tested in the following way: the initial values were distributed following the normal distribution law; 90 random initiators of the IPI and 10 opponents were selected out of all the subjects; the automaton was tested 100 times, each test run including 300 steps; average number of subjects in each of the states was determined. The initial personal opinion of the subject V_k about the information was distributed according to the normal distribution rule within the intervals $[-1; -0.5]$, $[-0.5; 0.5]$, $[0.5; 1]$. Trust level $TR_{kj}{}^{T_I}$ was distributed according to the normal distribution rule within the interval $[0; 1]$ or $[-1; 1]$. **Figures 7–9** demonstrate the functioning of the automaton.

Figure 7 demonstrates the functioning of the automaton, when $V_k \in [-0,5; 0,5]$, that is, most subjects are neutral to the IPI. **Figure 8** demonstrates the functioning of the automaton, when $V_k \in [-1; -0,5]$, that is, most subjects are negative to the IPI. **Figure 9** demonstrates the functioning of the automaton, when $V_k \in [0,5; 1]$, that is, most subjects are positive to the IPI. Figures "a" demonstrate the functioning of the automaton, when $TR_{kj}{}^{T_I} \in [0; 1]$, that is, the subjects adopt opinions of
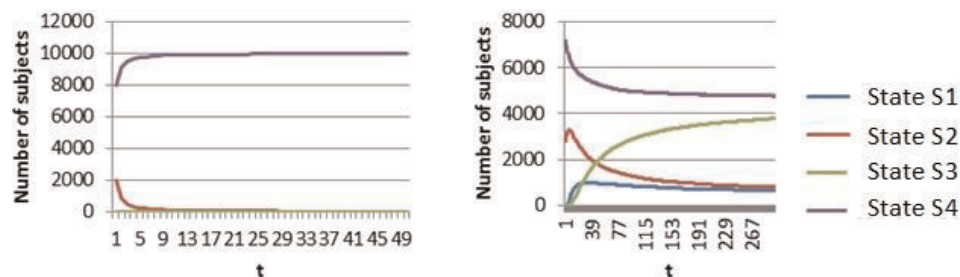

Figure 5.
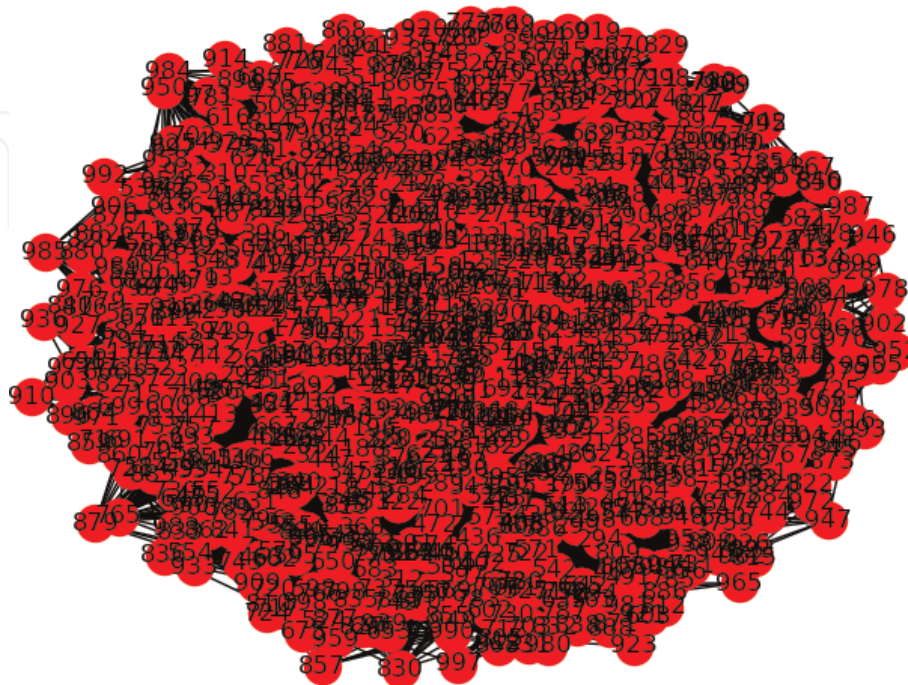*Distribution of cells according to the discrete time whenever $V_k \in [0,5; 1]$.*

Figure 6.
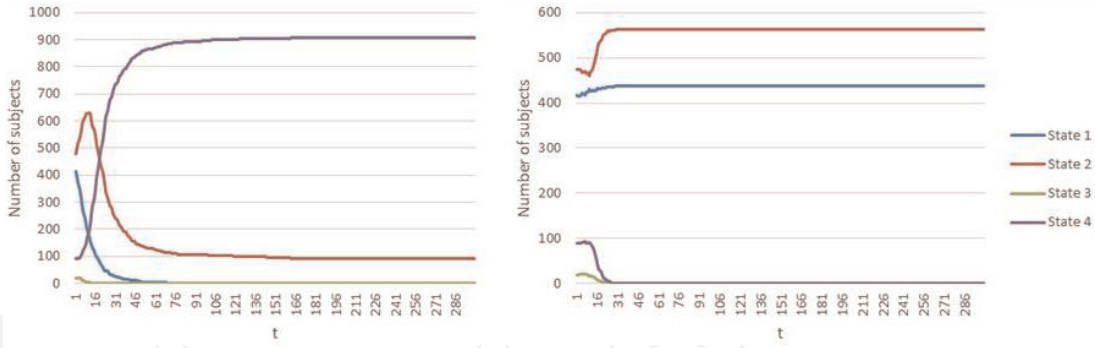*Random scale-free network generated by Barabási-Albert model.*

Figure 7.
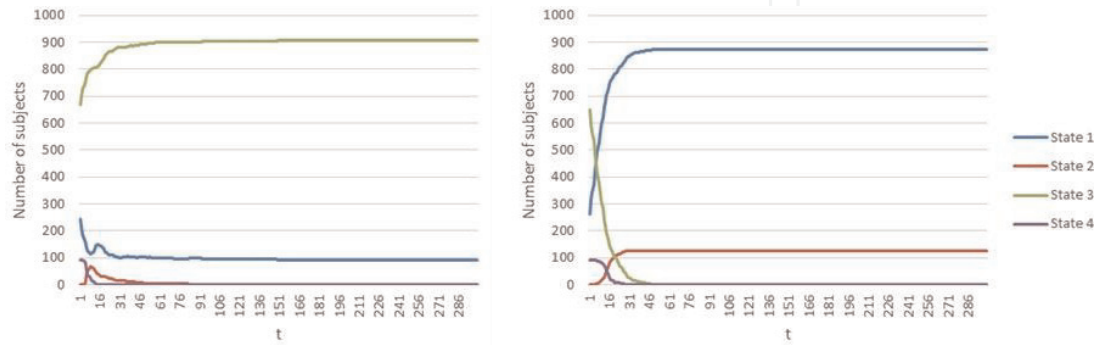*Distribution of cells according to the discrete time whenever $V_k \in [-0,5; 0,5]$.*

Figure 8.
Distribution of cells according to the discrete time whenever $V_k \in [-1; -0,5]$.
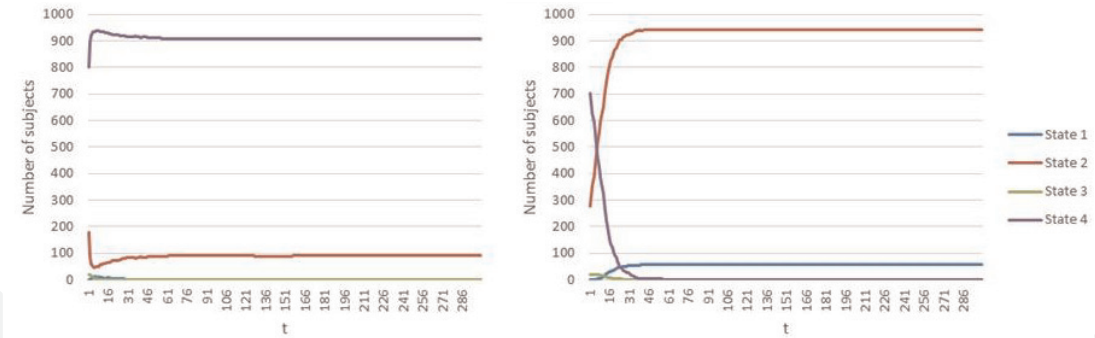

Figure 9.
Distribution of cells according to the discrete time whenever $V_k \in [0,5; 1]$.

other subjects. Figures "b" demonstrate the functioning of the automaton, when $TR_{kj}{}^{T_I} \in [-1; 1]$, that is, the subject has the opposite opinion to the one imposed by the IPI.

4.3 Discussion

Analysis of **Figures 3–9** shows that
  the character of the IPI diffusion within the social network is practically
    exponential;
  when the subjects are neutral to the IPI (**Figures 3a** and **7a**), just a small number
    of initiators can successfully perform the IPI;
  when the subjects are negative or positive to the IPI (**Figures 4a, 5a, 8a**, and **9a**),
    the IPI does not influence their state;

> when the subjects do not trust each other and change their opinions to the
> opposite ones (**Figures 3–5b** and **7–9b**), the number of subjects in states S3
> and S4 is similar, irrespective of their initial state.

The results obtained using the suggested models agree with the results presented in Refs. [4, 5, 30]. These works consider the information diffusion, which is an individual case of IPI diffusion in social networks. As opposed to Refs. [4, 5, 30, 39, 40], the suggested model is not based on the probabilistic characteristics of the subjects of the social network but takes into account the social and psychological parameters of the subjects and their psychological state during IPI diffusion in social networks.

5. Conclusion

The paper suggests a model for describing the diffusion process of information-psychological impact in social networks based on cellular automata. Cellular automata models can change the states of a large number of cells over a minimal period of time, which is very useful for the modelling of the process of information-psychological impact diffusion in social networks. The suggested models can thus represent the process of IPI diffusion in a social network and the corresponding changes in the opinions of its subjects caused by their immediate neighbours, taking into account social and psychological factors.

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