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Mathematical Model and General Trends for Information Dissemination in Social Systems

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***Abstract*—Information exchange is one of the essential processes in any social system. Contemporary channels of social communication and, primarily, the global information space (the Internet) and its social media are actively used to organize a range of activities which have an information and psychological impact on individual personality, social groups, and society as a whole. A well-known negative aspect of this practice is propaganda of extremist ideologies, terrorism, and other kinds of illegal activities. It is necessary to understand the nature of the information dissemination process in order to plan and carry out actions related to information management, as well as to identify and counteract destructive actions. This paper aims to develop a technique and model which would make it possible to study the patterns of information interaction in social systems. The paper presents a mathematical model for the information interaction process based on the theory of cellular automata and fuzzy cognitive modeling that makes it possible to formalize and consider the subjective qualities of communicators, the evaluation of which is given verbally. Taking into account the specifics of large-scale social systems and the complexity of obtaining and processing initial data for modeling them, a supplement to the model was suggested using representative sample data and statistical parameter distribution. Numerical experiments were performed to determine analytical dependencies between the parameters of the social system (connectivity, sensibility, sociability) and the dynamics of changes in opinions of agents in relation to the disseminated information.**

Keywords: social system, modeling, information interaction, theory of cellular automata, fuzzy sets, opinion distribution, information management.

I. INTRODUCTION

A person's social environment includes a number of social groups that influence that person's behavior and development. One of the fundamental processes taking place in any social system is the exchange of information. Technological progress, the emergence of new forms of social communication, and the respective intensification of information flows have a significant influence on this process.

A social system (SS) is a comprehensive entity; its main elements are people and their interactions, relationships, and connections. Traditionally, social systems are studied within social sciences (sociology, political science, social science, etc.). However, the processes taking place in SS have been attracting the attention of scientists within other disciplines, such as system analysis, mathematical modeling, information theory, etc. This is especially true for problems of information dissemination in a social environment.

Nowadays, channels of social communication and, primarily, the global information space (the Internet) and its social media are actively used to organize a range of activities which have an information and psychological impact on individual personality, social groups, and society as a whole [1]. A well-known negative aspect of this practice is propaganda of extremist ideologies, terrorism, and other illegal kinds of activities. So-called "information extremism" is becoming a pressing problem in modern society. Verbal forms of extremism begin to prevail over physical ones, and non-violent, hidden forms of extremism based on using modern means of communication and access to information resources are becoming more widespread, along with overt displays of aggression [2].

The advancement of information and communication technologies has influenced the processes of social communication, data exchange, education and socialization of an individual, and thus bolstered the arsenal of tools employed by extremists with various means of influence, such as information and psychological subversion, mind control, spread of rumors, and substitution of concepts and cultural values. The modern-day technical and technological environment provides powerful means to influence the consciousness of social groups by organizing and guiding processes of mass communication.

In order to develop counter-measures for destructive information activity, it is necessary to have a clear understanding of the mechanisms of information dissemination. Therefore, a pressing task is to develop algorithms and models that enable us to explore patterns of information interaction, monitor the "information background", and predict the public mood.

II. MATERIALS AND METHODS

A. *Information dissemination in social systems: features of the process*

Unlike traditional media (newspapers, radio, television), modern digital communication channels enable active participants of the information interaction process (IIP) to influence the political, economic and cultural life in a society by changing and transforming public opinion [3].

On the one hand, an opinion expressed by any communication participant impacts the information interaction process. On the other hand, each person individually decides whether the information they receive should be further disseminated or not. Therefore, modeling IIP requires taking individual characteristics of every participant into account.

Understanding the specifics of the information dissemination process enables decision makers to carry out various management actions in the SS, from implementing information support of certain legitimate trends to counteracting malicious content. In this case, information management is understood as an implicit indirect influence mechanism: the controlled object is provided with units of information that guide and incline it to take a certain behavior path [4].

B. *Modeling the process of information dissemination in social systems: existing approaches*

There is a range of research conducted by Russian and foreign scientists [5-14] analyzing the specifics of information interaction in social systems. The most complete and systematic consideration of this issue is presented in the work conducted at the Institute of Control Sciences of Russian Academy of Sciences (ICS RAS) under the general guidance of academic D. A. Novikov.

For example, [10, 11] describe a model of opinion dynamics formation based on Markov chain theory, in terms of a graph of communications, level of trust and reputation of interaction agents. In [12], threshold models of collective behavior are examined, where participants make decisions based on the behavior (observed or predicted) within their surroundings. Management, in general, consists in changing the degrees of influence, reputations and/or thresholds of communication participants.

However, these models do not reflect certain specific features of social systems that are relevant for applied research. They do not consider the subjective personal characteristics of communication participants that influence the IIP, such as different degrees of sociability, willingness to disseminate information, and susceptibility to external influence. Also, these models provide no means for studying and evaluating the speed of information dissemination in the SS, which is important for management planning.

Moreover, existing mathematical models are based on a number of strong assumptions, and their presence makes it difficult to use these models in applied research of real-life social interactions.

Thus, despite the fact that there already is a number of scientific papers considering this issue, creating IIP models that take the specific features mentioned above into account is still a pressing task.

The multi-agent approach is a promising area with regard to modeling processes taking place in the SS. Within its framework, system elements are analyzed as separate units interacting with each other. This makes it possible to study the properties of the social system as a whole, based on the parameters of its elements and rules of interaction between them.

However, it is necessary to take into account that people, which constitute a key element of social systems, bring a factor of subjective uncertainty into the processes of analyzing these systems. This makes it difficult to formalize modeling processes taking place in such systems [15]. Therefore, modeling IIP requires not only methods of probability theory and mathematical statistics, but also a special additional tool. For this, it is reasonable to use the apparatus of the theory of fuzzy sets and fuzzy cognitive modeling (FCM).

FCM makes it possible to assess more accurately and take into account the subjective characteristics of interaction agents that have no accurate quantification, and also to formalize verbal information.

C. *Required mathematical apparatus*

In order to formalize subjective data, it is proposed to introduce a linguistic variable (LV) – "Factor Level" – and to define a term-set of its values, which generally consists of several elements belonging to the negative and positive ranges of values.

For different factors, term-sets of three, five, or nine values are applicable:

$$\{low\ (L);\ average\ (A);\ high\ (H)\}; \tag{1}$$

$$\{low\ (L);\ below\_average\ (BA);\ average\ (A);\ above\_average\ (AA);\ high\ (H)\}; \tag{2}$$

$$\{strongly\_negative\ (H^-);\ negative\ (A^-);\ neutral\ (N);\ positive\ (A^+);\ strongly\_positive\ (H^+)\}; \tag{3}$$

$$\{strongly\_negative\ (H^-);\ above\_average\_negative\ (AA^-);\ average\_negative\ (A^-);\ below\_average\_negative\ (BA^-);\ neutral\ (N);\ below\_average\_positive\ (BA^+);\ average\_positive\ (A^+);\ above\_average\_positive\ (AA^+);\ strongly\_positive\ (H^+)\}. \tag{4}$$

Next, the term-set of LV values is mapped onto the set of fuzzy numbers specified by membership functions (MF) on an interval [-1; 1] of the real axis. As a family of membership functions for the term-set of a linguistic variable with nine elements, we can use a nine-level classifier in which the corresponding membership functions for fuzzy numbers are trapezoids:

$$\{H^-(-1;-1;-0,85;-0,75);\ AA^-(-0,85;-0,75;-0,65;-0,55);\ A^-(-0,65;-0,55;-0,45;-0,35);\ BA^-(-0,45;-0,35;-0,25;-0,15);\ N(-0,25;-0,15;0,15;0,25);\ BA^+(0,15;0,25;0,35;0,45);\ A^+(0,35;0,45;0,55;0,65);\ AA^+(0,55;0,65;0,75;0,85);\ H^+(0,75;0,85;1;1)\}, \tag{5}$$

where in a fuzzy trapezoid number $X(a_1, a_2, a_3, a_4)$, a_1 and a_4 are abscissas of the lower base, and a_2 and $a_3$are abscissas of the upper base of the trapezoid.

The proposed classifier projects a fuzzy linguistic description of a factor onto the interval [-1; 1] in a consistent way, placing the classification nodes symmetrically [16].

Based on the results of the theory of fuzzy sets and fuzzy cognitive modeling in describing the process of information dissemination in social systems, we propose taking into account the following personal parameters that describe SS members:

- The "conservatism level" is a parameter expressing the ability to maintain one's opinion under the influence of information background. The "high conservatism" value corresponds to the tendency to always keep to one's initial opinion, "low conservatism" means a high degree of conformity (tendency to change one's point of view, adjust to the opinions of others). The opposite indicator of conservatism can be called the coefficient of susceptibility to another's opinion (conformism indicator). In some cases, this parameter is more convenient to be used in calculations.

- The probability that a person will disseminate any information they receive largely depends on the level of personal communicability (sociability). Various psychological tests can be used to determine the level of sociability, such as the well-known Assessment of Sociability Level by V. F. Ryakhovsky, which consists of 16 questions and evaluates sociability according to the scores obtained [17]. The test uses seven degrees of sociability, ranging from explicit non-communicability to abnormal communicability.
- It is also necessary to identify a list of subjects that are relevant to the members of the SS being studied (or, on the contrary, subjects that will not find any response from SS participants in the information dissemination process). This will make it possible to draw conclusions about the level of interest, as well as the distribution of initial opinions regarding the information disseminated.
- The degree of trust that the information interaction (II) process participant has in the sources reflects the credibility of the information exchange agents that provided the information.

If we represent information interaction in a SS consisting of *N* members as a graph *S*=(*M*, *D*) where the vertices denote people $M=\{M_1; M_2;...; M_N\}$, then the set of its edges $D=\{D_{ij}\}$ reflecting a probable information exchange between them forms an "information exchange matrix":

$$D_{ij} = \begin{cases} 1, & if\ Mi\ communicates\ with\ Mj; \\ 0, & if\ Mi\ does\ not\ communicate\ with\ Mj \end{cases} \quad (6)$$

The most important characteristic of such a graph is the distribution of nodes by the number of connections – the number of "contacts" of an II participant.

Information interaction in a SS is also characterized by trust matrix T^I for the subject being examined *I*. Its elements can be expressed by fuzzy numbers. However, both the trust matrix and the information exchange matrix are not necessarily symmetrical: if participant *j* shares information with participant *i* or trusts them, the latter will not necessarily act the same way in response. A perfect example of such a situation is information distribution by mass media; in this case, the information interaction is strictly one-directional in nature.

The main cause of asymmetry of these matrices is the difference in conservatism and sociability levels of the II participants.

An important dynamic indicator of an IIP is the change in the number of participants informed, which is expressed using an information awareness vector. In IIP modeling, the reception of information by the *i*th participant is reflected by changing the corresponding coordinate in the information awareness vector $Z(Z_1; Z_2; \ldots; Z_N)$ from 0 to 1:

$$Z_i = \begin{cases} 1, & if\ Mi\ has\ the\ information; \\ 0, & if\ Mi\ does\ not\ have\ the\ information \end{cases} \quad (7)$$

The "information transfer indicator" by the *i*th agent ("repost indicator") reflects the agent's willingness to disseminate information. This dynamic indicator depends both on the sociability level of the communication participant O_i and on the strength of their current opinion. The repost indicator is 0 if the degree of sociability is determined as *L* (Low) from the term-set (1) or if the agent has a weakly expressed negative (A^-), neutral (*N*), or weakly expressed positive (A^+) attitude towards the information *I*, which does not lead to its further dissemination. Information transfer indicators are collectively represented by repost vector $R(R_1; R_2; \ldots; R_N)$.

D. Model of information dissemination in social systems

Let's consider the information interaction process in a SS. The information unit *I*, having a certain subject, is introduced into the social environment at the initial instant in time *t*=0 by a finite number of its representatives $\bar{M} = \{\bar{M}_l\}$ $(l = \overline{1; L}, L < N)$ with an inherently positive (or negative) attitude to *I*. The $\bar{M}$ set will hereinafter be called the initiating set (IS).

Interpersonal information exchange ensures the dissemination of information between participants. During this process, participant *j* possessing information *I* brings it to the attention of participant *i* along with their own opinion on this information.

Taking into account the considerations above, we propose using the following formulas to estimate the current (at discrete instant in time *t*=*t*+1) attitude $\tilde{V}_i^{t+1}$ of participant *i* of the SS to information *I* after exchanging views with other participants:

$$\tilde{V}_i^{t+1} = C_i^I \cdot \tilde{V}_i^t + (1 - C_i^I) \cdot CSP_i^{t+1}, \quad (8)$$

$$\bar{V}_i^{t+1} = \begin{cases} 1, & at\ \ Def[\tilde{V}_i^{t+1}] \geq 1; \\ Def[\tilde{V}], & at -1 < Def[\tilde{V}_i^{t+1}] < 1; \\ -1, & at\ \ Def[\tilde{V}_i^{t+1}] \leq -1 \end{cases} \quad (9)$$

Here, $\tilde{V}_i^{t+1}$ is the fuzzy value of the attitude of participant M_i to information *I* at a discrete instant in time (*t*+1). An opinion can be evaluated by a value from a term-set (4), which can subsequently be mapped to a number from a fuzzy classifier (5);

$\bar{V}_i^{t+1} \in [-1; 1]$ – the defuzzified (explicit) value of M_i's attitude to information *I* at a discrete instant in time (*t*+1). In order to defuzzify a fuzzy value, the "gravity center" method is used;

C_i^I – the coefficient of conservatism of participant M_i reflecting how strongly they rely on their own opinion in relation to the subject *I*. It should be noted that the closer the average value $C^I = \frac{1}{N}\sum_{i=1}^{N} C_i^I$ to 1, the more conservative the "collective opinion" is on the subject *I*.

The information that is made known to agent M_i by others at (*t*+1) and that contributes to a change in the agent's opinion is reflected by a parameter called Cumulative Social Power, or CSP (the term was introduced in [18]). It is proposed to use the following formula to calculate this:

$$CSP_i^{t+1} = \frac{W_i^+ + W_i^-}{G}, \quad (10)$$

where W_i^+ and W_i^- are sums of the positive and negative opinions expressed by other participants at (t+1), weighted by the degree of trust in the information source; $G = N_{t+1}^+ + N_{t+1}^-$ is the number of positive and negative feedback entries received at (t+1) for information I respectively.

$$W_i^+ = \sum_{j=1}^{N^+} (T_{ij}^I \cdot W_{ij}^+), \quad (11)$$

$$W_i^- = \sum_{k=1}^{N^-} (T_{ik}^I \cdot W_{ik}^-), \quad (12)$$

where W_{ij}^+ is a positive opinion received by M_i from participant j at (t+1); W_{ik}^- is a negative opinion received by M_i from participant k at (t+1).

The resulting explicit values $\bar{V}_i^{t+1}$ are interpreted using the Harrington scale, as follows:

$-1 \le \bar{V}_i^{t+1} \le -0{,}64$ – strongly expressed negative attitude, encouraging dissemination of information I together with a negative opinion given by the participant (negative assessment) (communication participant state: S=S^-);

$-0{,}64 < \bar{V}_i^{t+1} < 0{,}64$ – weakly expressed negative ($-0{,}64 < \bar{V}_i^{t+1} < 0$) or weakly expressed positive ($0 < \bar{V}_i^{t+1} < 0{,}64$) attitude to I, which does not lead to further dissemination of information (state S=S^0);

$0{,}64 \le \bar{V}_i^{t+1} \le 1$ – strongly expressed positive attitude, encouraging dissemination of information I together with a positive opinion given by the participant (positive assessment) (state S=S^+).

Set $\bar{V}_I^{t+1} = \{\bar{V}_i^{t+1}\}$ reflects the "spectrum of views" of the SS members regarding information I at t+1. The statistical parameters for distributions of opinion spectra for different information blocks reflect the moods prevailing in the SS and allow to monitor them.

The information exchange process is terminated if the Hamming distance ρ_H between the current vector $\bar{V}_I^{t+1}$ and the vector $\bar{V}_I^t$ obtained at the previous time step does not exceed a certain value N^* (which is set before launching the simulation):

$$\rho_H(\bar{V}_I^{t+1}; \bar{V}_I^t) \le N^*. \quad (13)$$

The Hamming distance $\rho_H \in [0; N]$ corresponds to the number of communication participants that had changed their minds between two consecutive time steps. When ρ_H becomes insignificant, the discussion of information block I in the social environment is considered to be over.

E. *Algorithm for simulation modeling of the information interaction process*

Taking the considerations given above into account, we propose the following algorithm for simulating IIP taking place in a social system:

- Formation of an information block I, related to a specific topic, for further dissemination during the II process.
- Calculation of the initial vector of opinions of participants $\tilde{V}_I^0$ at step t=0.
- Setting the size L of the initiating set consisting of participants with a pre-determinedly strongly positive (or negative) opinion towards information I.
- Formation of an initial awareness vector Z where awareness indices for the members of the initiating set $\bar{M}$ are equal to 1, indices for other participants are 0.
- Launching the information exchange iteration at time step t=t+1.
- Formation of the repost vector R.
- Transmission of information I from agents with repost indicator equal to 1 towards other participants according to the information exchange matrix D; calculation of the current awareness vector Z.
- Calculation of the current opinion vector $\tilde{V}_I^{t+1}$.
- Calculation of the Hamming distance ρ_H between the current vector $\bar{V}_I^{t+1}$ and the vector $\bar{V}_I^t$ obtained at the previous simulation iteration.
- Hamming distance verification: if $\rho_H \le N^*$, then simulation stops and the data is displayed for further analysis; otherwise, simulation returns to step 5.

The single simulation step (iteration) is set to the time interval required for a singular implementation of all communication links reflected in the exchange matrix D.

F. *Specifics of modeling the information interaction process in large social systems*

By applying the algorithm given above, we can estimate the speed of information dissemination in the SS (increase in the number of informed participants), as well as trace the dynamics of agents' opinions regarding the information disseminated. However, this requires initial data on SS structure and composition, as well as data on individual characteristics of the persons (information interaction participants).

For relatively small social systems with less then a few hundred members, obtaining the raw data is usually not very challenging. Such information is deterministic (not probabilistic) in nature. For example, in small organizations, the information exchange matrix, the level of employee interest in the information being disseminated, and the degree of trust in its source within the scope of certain topics can be obtained directly by analyzing data provided by the Human Resources department. The efficiency of this approach in small organizations had been proven during practical verification of the adequacy of the proposed model and algorithm while planning activities related to information influence upon personnel [19, 20].

However, studying the IIP in larger social systems (such as social networks) means having to deal with much higher amounts of data [21]. Moreover, in most of these cases, the personal data of the information interaction participants is confidential and cannot be legally obtained without their consent.

Thus, in contrast to information dissemination within a small SS, the exact values for simulating IIP in large social systems are difficult to obtain. The source data in such cases can be stripped of personal information and provide only statistical values (parameters of statistical distributions). Sometimes this can be found in analytical reports regarding the structure and composition of social networks used as communication channels (see, for example, [22,23]).

In order to obtain the rest of the information necessary for IIP simulation, a technique was proposed that involves studying a representative sample of the general population of interaction participants. In this case, the distributions of SS agent parameters obtained for a representative sample are enough to restore the corresponding characteristics of the entire system. The proposed method, for example, made it possible to obtain data about users of the VK social network living in the Chechen Republic [24].

Since the source data for IIP simulation in large SS are only statistical in nature, it is proposed to make some additions to the above simulation algorithm in order to estimate the number of informed participants at each simulation step, as well as the number of different opinions among participants regarding the information being disseminated [25].

First of all, since the total number of informed agents at each modeling cycle (discussion step) is largely determined by the number of their connections, we will study the representative sample in order to determine the statistical distribution of the number of contacts ("friends") with which the SS participants interact.

In this case, it is reasonable to identify several intervals of the possible number of connections $\{b_i^{min} \dots b_i^{max}\}, i = \overline{1,n}$, and, respectively, n categories of II participants falling into these communication boundaries. The distribution of the number of connections in the SS is expressed by a percentage of agents in each of the categories $\beta_i, i = \overline{1,n}$.

The process of information exchange between agents is subject to the following rules:

- Only agents with a high communicability (sociability) factor O_i share information.
- Only agents with a strong (positive or negative) attitude towards certain information disseminate this information together with their own opinion on it.

Initially, the number of informed participants is supposed to be equal to the initializing set size L from the general population N. In this case, if the purpose of information dissemination is controlling influence, then IS is formed in such a way that its members have mostly positive (or negative) attitude towards the information unit being introduced, have extensive connections, were quite sociable and were trusted by the II participants.

After the first iteration of the discussion, the number of participants possessing information I is determined as follows:

$$K_1 = L + \left(\frac{N-L}{N}\right) \cdot L \sum_{i=1}^{n} \beta_i \bar{b}_i, \qquad (14)$$

where $\bar{b}_i$ is the average value of the number of connections in the i-th range.

The $(N\text{-}L)/N$ factor represents the proportion of II participants that remain uninformed at a given iteration. This makes it possible to exclude the participants that have already received the information from calculations (although the opinion of the agents may change).

At the time step t=t+1, the number of informed SS participants can be represented as:

$$K_{t+1} = K_t + q_t \cdot \left(\frac{N-K_t}{N}\right) \cdot (K_t^{++} + K_t^{--}) \cdot \sum_{i=1}^{n} \beta_i \bar{b}_i, \quad (15)$$

where K_t^{++} and K_t^{--} are the numbers of agents with a strong positive and negative opinion at the previous time step; q_t is the proportion of agents in step t prepared to further disseminate the information (repost it).

The value of the q_t factor from (15) depends on the percent of II participants with a high level of sociability (*Com*), as well as on relevance of the information being disseminated at the time step t (Act_t).

Since the sociability level is an inherent (intrinsic) characteristic of SS participants, we can consider the *Com* proportion of II participants with high sociability levels to be constant (independent of time t).

On the other hand, the relevance of the information disseminated in the II process decreases with time. Hence, the following formula for q_t was proposed:

$$q_t = Com \cdot Act_t = Com \cdot Act_0 \cdot e^{-\alpha \cdot t / \tau_{act}}, \qquad (16)$$

where Act_0 is the initial (at t=0) information relevance, which is usually set to 1; relevance decline factor (according to numerous studies, e. g. [26], α=2.3); τ_{act} is the maximum time for the information disseminated to maintain its relevance (information lifecycle duration).

It should be noted that (15) defines the upper bound of the awareness function. In a real-life social system, the number of agents newly informed at each step may be lower due to the fact that some II participants will receive information from different sources at the same time.

Thus, the number of informed members of the social system can be represented as a function

$$K_{(t+1)} = K_{(t+1)}\left(L, q_t, \bar{b}, K_{(t)}\right), \qquad (17)$$

where $\bar{b}$ is the SS connectivity factor (average number of connections between the II participants in the system).

The formation of opinions during information exchange depends on the susceptibility of participants to the information background. The "factor of susceptibility to others' opinions" parameter (conformity/suggestibility factor) for the II participants can be evalyated by a value from the following term-set: {low (L); average (A); high (H)}. Respectively, the proportions of agents with different degrees of susceptibility will be denoted as $\omega^L, \omega^A, \omega^H$.

We will use values from the term-set (3) to evaluate opinions of the participants. We shall introduce the following notation:

K^{++} is the number of agents with a strong positive opinion (the proportion is $\nu_t^{++} = K_t^{++}/K_t$);

K^+ is the number of agents with a positive opinion (the proportion is $\nu_t^+ = K_t^+/K_t$);

K^N is the number of agents with a neutral attitude ($\nu_t^N = K_t^N/K_t$);

K^- is the number of agents with a negative attitude ($\nu_t^- = K_t^-/K_t$);

K^{--} is the number of agents with a strong negative attitude ($\nu_t^{--} = K_t^{--}/K_t$).

The initial distribution of opinions in a social system is determined by the data for a representative sample.

We shall define the following rules that affect the opinion dynamics in a SS:

- Opinions of participants with low susceptibility do not change.
- Participants with medium and high susceptibility change their opinions upon receiving emotionally charged feedback.
- Persons with medium to high susceptibility "leave" (are subtracted from) categories of participants with strongly expressed opinions upon receiving feedback that goes against their beliefs. Participants with medium susceptibility form a positive or a negative opinion; participants with high susceptibility become neutral.
- Participants from the "neutral" group with high susceptibility form a strongly expressed opinion (either positive or negative) upon receiving respective feedback.
- "Neutral" participants with medium susceptibility acquire a positive or a negative opinion in accordance with the feedback received.
- Participants with a positive opinion and medium or high susceptibility form a strongly expressed positive opinion upon receiving positive feedback.
- Participants with a negative opinion and medium or high susceptibility form a strongly expressed negative opinion upon receiving negative feedback.
- Participants with a positive opinion and medium susceptibility become neutral upon receiving negative feedback. If their susceptibility is high, they form a negative opinion.
- Similarly, participants with a negative opinion and medium susceptibility become neutral upon receiving positive feedback. If their susceptibility is high, they form a positive opinion.

Taking these rules into account, the number of agents with a strongly expressed positive opinion at modeling step *t*=*t*+1 can be expressed as follows:

$$K_{t+1}^{++} = K_t^{++} + (K_{t+1} - K_t) \cdot [\nu_0^{++} - \nu_0^{++} \cdot (\omega^A + \omega^H) \cdot \left(\frac{K_t^{--}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{+} \cdot (\omega^A + \omega^H) \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{N} \cdot \omega^H \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right)] \tag{18}$$

Factors $\frac{K_t^{++}}{K_t^{++}+K_t^{--}}$ and $\frac{K_t^{--}}{K_t^{++}+K_t^{--}}$ reflect the proportions of II participants sharing strongly expressed positive and negative opinions respectively.

This formula has the following meaningful interpretation:

- the proportion of informed participants with a strongly expressed positive opinion is ν_0^{++};
- agents with a neutral attitude and high susceptibility and participants with a positive attitude also form a strongly expressed positive opinion upon receiving positive feedback;
- the number of participants with a strongly positive opinion who are affected by "neighbors" sharing a negative attitude is to be subtracted.

The number of participants with a positive opinion, in accordance with the rules of IIP agent behavior, is calculated as follows:

$$K_{t+1}^{+} = K_t^{+} + (K_{t+1} - K_t) \cdot [\nu_0^{+} - \nu_0^{+} \cdot (\omega^A + \omega^H) \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right) - \nu_0^{+} \cdot (\omega^A + \omega^H) \cdot \left(\frac{K_t^{--}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{++} \cdot \omega^A \cdot \left(\frac{K^{--}}{K^{++}+K^{--}}\right) + \nu_0^{-} \cdot \omega^H \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right) + \cdot\, \nu_0^{N} \cdot \omega^A \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right)] \tag{19}$$

The category of participants with a neutral attitude to *I* is formed as follows:

$$K_{t+1}^{N} = K_t^{N} + (K_{t+1} - K_t) \cdot [\nu_0^{N} - \nu_0^{N} \cdot (\omega^A + \omega^H) + \nu_0^{-} \cdot \omega^A \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{+} \cdot \omega^A \cdot \left(\frac{K_t^{--}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{++} \cdot \omega^H \cdot \left(\frac{K_t^{--}}{K_t^{++}+K_t^{--}}\right) + \nu_0^{--} \cdot \omega^H \cdot \left(\frac{K_t^{++}}{K_t^{++}+K_t^{--}}\right)] \tag{20}$$

The number of SS participants with negative and strongly negative opinions is determined by formulas similar to (18) and (19).

III. RESULTS

In order to identify the general patterns of information interaction in social environments, the corresponding software has been developed to implement the models and algorithms presented above.

Numerical experiments were carried out in a social system with the population taken as 10 million using the following initial data:

- number of connections: from 1 to 5 – 82% of participants, from 6 to 30 – 17%, more than 30 and less than 100 – 1%; the average number of contacts per person – 6.2;
- susceptibility: $\omega^L = 0{,}2, \omega^A = 0{,}55, \omega^H = 0{,}25$;
- initial attitude to the subject under study: $\nu_0^{++} = \nu_0^{--} = 0{,}05$, $\nu_0^{+} = \nu_0^{-} = 0{,}15$, $\nu_0^{N} = 0{,}6$ (predominantly neutral equilibrium environment);
- willingness to disseminate the information received: $q_0 = 0{,}4$.

The information block was introduced into the system through an initiating set of 0.01% of the general population (1000 people with a highly positive attitude towards this information).

The dynamics of the information exchange process is shown in Fig. 1. The sigmoid shape of the plots suggests three IIP stages.

During the first stage, the number of informed SS members is increasing slowly. Then, after a certain point in time, a sharp exponential growth begins in the number of participants who have received the information. After that, the process slows down and moves to the third stage, where further information transfer is almost non-existent. It is important to note that full SS awareness is never reached. Opinion exchange between participants may continue for some time, but the established balance of views does not change significantly.

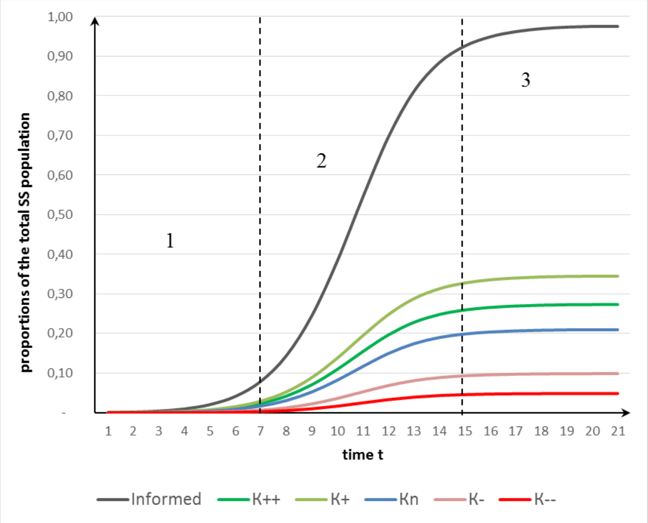

Fig. 1. Graphs showing increase in the number of informed participants and the distributions of their opinions

This visual representation of the II process based on the given model reveals important analytical relationships between parameters of social systems (connectivity, susceptibility, sociability) and information exchange dynamics.

For example, a decrease in q_0 to 0.35 significantly reduces the overall awareness among members of the social system, although it does not affect the relative distribution of their opinions (Fig. 2).

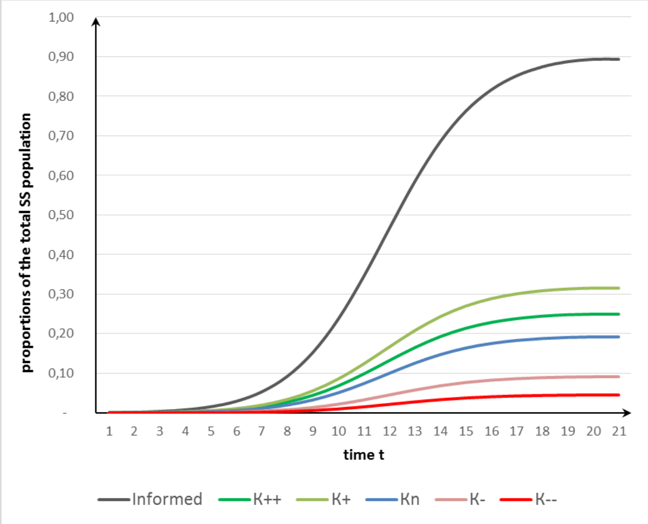

Fig. 2. IIP graphs: at q_0=0.35

A decrease in SS susceptibility to the information background leads to both a decrease in awareness and a shift in the ratio of participants' opinions regarding the information received (see the graphs of neutral and strongly positive opinions in Fig. 3).

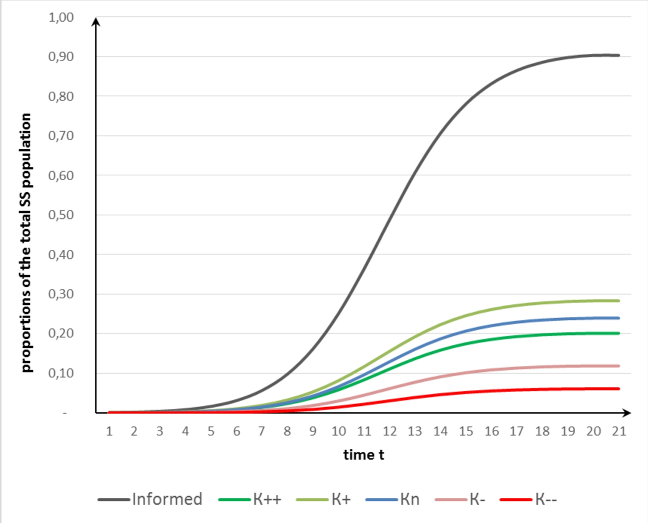

Fig. 3. IIP graphs: at $\boldsymbol{\omega^L = 0,3, \omega^A = 0,5, \omega^H = 0,2}$

IV. Discussion

The practical value of the model lies in its ability to predict the development of a situation and public response during various information activities (including destructive ones), and, more importantly, consider opportunities and consequences of targeted intervention within the information dissemination process for the purpose of controlling influence.

As an example, here are some possible ways to influence a social system in order to change its parameters:

Discrediting the source of the destructive information disseminated, which will lead to a decrease in its credibility and susceptibility to it.

Initiating and launching another information unit that draws the attention of communication participants from the initial destructive information, reducing its relevance and readiness to distribute it.

Obviously, the counteraction measures will be most efficient at the initial stage of malicious information dissemination, before the process enters the fast growth stage.

V. Conclusion

The advancement of communication technologies has significantly diversified the possible ways of presenting information to society. Today, the achievements of science and technology are used not only for good, but also for illegal activities carried out by various extremist and terrorist organizations. Information management measures should become an adequate response to destructive processes caused by actions of such kind.

Simulation of the information interaction process makes it possible to investigate the patterns of information dissemination and dynamics of opinion formation in social systems, predicting the public response to the publication of certain information, and taking measures to regulate and stabilize the information background, which, in turn, helps to reduce manifestations of anti-social behavior.

Prospective areas for development are to continue research aimed at identifying and studying the analytical relationships between parameters of a social system and the dynamics of the information exchange process within it, as well as opportunities for targeted management intervention in this process.

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