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MODELING SOCIAL ATTITUDE TO INTRODUCING EPIDEMIC SAFETY MEASURES IN A PANDEMIC[1]

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Abstract. The COVID-19 pandemic is a global human-scale emergency that has caused many negative effects. To mitigate them, it is necessary to take competent and well-founded organizational measures. Considering infectious diseases from a mathematical point of view allows solving problems in various spheres of society, studying possible scenarios, identifying epidemiological evolution patterns, and proposing intervention strategies and epidemic control actions. This paper presents a mathematical model for forecasting opinion dynamics on various socially significant issues, in particular, on the introduction of epidemic safety measures in a pandemic. The model reflects the process of information exchange considering the content of disseminated information and the communicative properties of the social system and its elements (connectivity, susceptibility, and sociability).

Keywords: social system, process modeling, informational control, distribution of opinions, anti-epidemic measures.

INTRODUCTION

In the last few years, there has been a concept in the information space whose social significance seems difficult to exaggerate: pandemic. It is defined as the intensity of an epidemic process characterized by the mass spread of an infectious disease in several countries or even continents.

The COVID-19 infection faced by mankind has several features causing numerous difficulties in diagnosis and treatment, as well as in forecasting the development and making timely organizational and managerial decisions, particularly at the regional level.

The key problem is the absence of accumulated statistical data. The frequent mutation of this virus and asymptomatic and mild cases considerably complicate analytical studies [1].

In addition to the epidemiological characteristics of a pandemic and the socio-demographic structure of the population, the indicators of pandemic development depend on many other factors, especially, on the prevention and treatment measures taken by the healthcare system, the attitude to them in society, and the social position of the majority.

Despite these difficulties, attempts are undertaken to develop a mathematical framework and software to model the real epidemiological and socio-economic situation in a region and to forecast its dynamics and the consequences of certain planned measures. Considering infectious disease models allows conducting computational experiments, studying possible scenarios, identifying epidemiological evolution patterns, and proposing intervention strategies and epidemic control actions.

1. MODELS TO DESCRIBE AND FORECAST EPIDEMICS

Modeling may aim at short- or long-term forecasting of the epidemiological situation, assessing the nature and dynamics of the infection spread, identifying key time periods (the peaks of incidence, reaching a

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plateau, and decay), and testing of anti-epidemic measures. Depending on the problems formulated, researchers prefer one or another type of models [2, 3].

There are analysis methods based on considering epidemic processes in continuous and discrete time, at the level of interaction between population groups separated by different attributes and individuals [4].

A “gold standard” in describing epidemics is the SIR chamber model and its modifications. According to this concept, a population is divided into groups (chambers) depending on the state (the stage of the disease). Different modifications of this model include three to seven groups are follows: *S* (Susceptible), *E* (Exposed, in the incubation period), *I* (Infected, with symptoms), *R* (Recovered), *H* (Hospitalized, with severe disease dynamics), *C* (Critical, requiring a lung ventilator), and *D* (Deaths).

Over time, the status of individuals changes and they pass from one group to another. Thus, nowadays, there exists a whole family of models of this class with different sets of chambers: SIR, SIS (without immunity production), SIRS (with temporary immunity), SEIR, SIRD, SEIRD, and SEIR-HCD [5].

The mathematical model represents a system of nonlinear partial differential equations with initial and boundary-value conditions [6]. The parameters of SIR models determine the frequency and probability of transitions between groups, i.e., the rates of recovery and re-infection, the frequency of symptoms, the probability of hospitalization, the disconnection of the lung ventilator, etc.

These indicators are calculated based on the demographic and geographic characteristics of the territory under consideration (country, region, or city), ideally considering multiple factors (the type of disease, the probability of virus mutations, population density, mobility, age, average immunity level, and climate) [7].

The main problem of chamber models is that their output results have high sensitivity to variations in their input parameters. The lack of reliable statistical data significantly reduces the quality of forecasting.

Agent-based models are more detailed than chamber models. In such models, each participant is considered individually taking into account its social links. Agents also go through disease stages, but all transitions are modeled at the individual level rather than at the group level. As a result, population heterogeneity can be studied in terms of different personal characteristics, e.g., basic health level and the number of social contacts. To succeed in developing a model of this class, it is necessary to represent the structure of the modeled system and to simulate the actions of agents with sufficient accuracy [8].

In the class of so-called reaction-diffusion epidemiological models, the spread of viral infection is described by a system of heat conduction equations. They assume the non-uniform spatial distribution of participants but an instantaneous virus transmission without any incubation period [9].

Regression and time series analysis methods are well known to forecast morbidity (incidence rate). In particular, we note ARIMA, an integrated autoregression model. It is a class of parametric models describing nonstationary time series. However, the absence of reliable statistics for the past periods significantly restricts the application of this approach.

2. INFORMATIONAL INFLUENCE AND CONTROL IN EPIDEMIOLOGICAL EVOLUTION

To improve the efficiency and adequacy of models, it is necessary to consider the influence of administrative measures intended to limit the virus spread.

Such measures include social distancing, self-isolation, cancellation of mass events, blocking of transportation flows, remote production and training, and wearing masks and gloves in public places. They reduce the quality of life, worsen the psychological state of people, and may cause negative reactions [10–12].

The efficiency of quarantine measures largely depends on the discipline of the population [13]. Therefore, they should be introduced considering special mathematical models-based assessments with additional input data related to social processes rather than to medical aspects.

Several years before the global spread of COVID-19, models were developed to determine possible human behavior under various countermeasures for diseases [14, 15]. The corresponding research aimed to develop disease control strategies and assess different intervention actions [16]. The studies of behavioral incentives identified an obvious correlation between epidemiological and economic indicators [17]. Thus, when determining the influence of various restrictive measures on epidemiological evolution, it is necessary to consider the degree of their public support or rejection.

Domestic and foreign researchers investigate the processes of information dissemination in social systems and the influence of various factors on the formation of opinions (beliefs and attitudes) in society.

The general patterns of opinion dynamics (agreement and convergence, divergence and polarization) were considered and justified in [18, 19]. The factors determining the value and attractiveness of information, various personal characteristics reflecting the internal state and responsible for the external behavior of people, as well as the rules of information transfer in communication processes were identified and assessed in [20, 21].

Many publications have been devoted to the problems of informational control, i.e., planning and organization of indirect and implicit influences to distribute information that inclines social system participants to choose a required line of behavior [22]. Different strategies have been proposed to regulate public opinion on significant issues (in particular, the identification and use of critical points of social networks, the so-called "opinion leaders" [23, 24]).

The models of informational influence proceed from various basic theoretical assumptions and hypotheses: linear threshold models, independent cascade models, models with biological and thermodynamic analogies ("contamination" and "magnetization"), cellular automata models, Markov chain models, and game-theoretic models. Each model mentioned has specific advantages in a particular sphere; at the same time, mathematical models are often based on several assumptions, which can complicate their use in the applied research of real social interactions [25–27].

In what follows, we propose a mathematical model of information exchange in a social system based on aggregated indicators (probability distributions). The model considers the content of the information block disseminated and some communication properties of the social system and its elements (the number of connections, susceptibility, and sociability).

This model can be used to forecast the distribution of opinions in society on the disseminated information about the introduction of epidemic safety measures in a pandemic as well as to elaborate managerial decisions toward increasing the public awareness of the importance of anti-epidemic measures.

3. MATHEMATICAL MODEL TO FORECAST OPINION DYNAMICS IN SOCIETY

The population living in a certain region is a social system characterized by connectivity (the average number of social contacts), sociability, and susceptibility of its elements (individuals) to some information. Sociability is the desire to share the information received, while susceptibility is the inclination of an individual to change his (or her) point of view under the influence of others.

The model parameters related to the individual's characteristics cannot be quantified precisely. Therefore, these data are formalized by introducing a distribution with a value set consisting of three or five categories as follows:

$$\{\text{low } (L);\ \text{moderate } (M);\ \text{high } (H)\}; \tag{1}$$

$$\begin{gathered}\{\text{strongly negative } (--);\ \text{negative } (-);\\ \text{neutral } (N);\ \text{positive } (+);\\ \text{strongly positive } (++)\}.\end{gathered} \tag{2}$$

The characteristics of large social systems are determined in the form of statistical distributions. To obtain initial data, we propose a methodology of social system research based on representative sampling. A special questionnaire with a set of direct and indirect questions is used to establish:

– the average number of contacts per individual;

– the level of sociability of the participants;

– the susceptibility indicators of social system's participants, estimated in terms of the set (1), i.e., as the corresponding shares of the total number (ω^L, ω^M, and ω^H);

– the initial distribution of opinions on a given issue (fuzzy assessments from the set (2)) as the corresponding shares ν_0^{--}, ν_0^{-}, ν_0^{N}, ν_0^{+}, and ν_0^{++}.

The social system's participants are represented as separate and interacting elements (agents). Information is disseminated in the system through interpersonal data exchange. By assumption, the behavior of participants obeys the following rules:

▪ Participants with a high level of sociability and a pronounced (positive or negative) attitude toward the information received share this information.

▪ During information exchange, the participants with medium and high susceptibility change their opinions under the impact of others when receiving emotionally colored feedback; in the latter case, the opinion can change dramatically (e.g., from positive to negative or from strongly negative to neutral).

Information interaction starts at step $t = 0$, when information is introduced into the social system through the so-called initiating set (a finite number of its representatives who have received information from the primary source). The goal of modeling is to calculate the share of participants who have received information and the distribution of their opinions at each step $t = t + 1$. One step is the time required for the single implementation of all communicative links between the participants.

Social information dissemination processes can be studied using a multidisciplinary approach (mathematics, sociology, and psychology of communication) to solve a wide range of related problems. In particular, the coverage of the target audience by various alarm means in an emergency was determined in the earlier paper [28]. The goal was to develop a methodology for selecting and justifying the parameters of disseminated information blocks as well as their structure and content considering the socio-psychological features of their perception. The emotional component of the social opinion about the threats of emergencies and their consequences was quite obvious. When disseminating information, the understanding of its utility and necessity in several categories ("harmful," "neutral," and "useful") came to the fore.

The number K_{t+1} of informed participants at each interaction step (t + 1) was analytically expressed through the following parameters:

- L, the size of the initiating set;
- $\bar{b}$, the connectivity coefficient of the social system (the average number of links between its members);
- K_t, the number of informed participants at the previous step t;
- q_t, the share of participants willing to share the information received at step t.

The value q_t depends on the share of participants with a high level of sociability and on the relevance of the disseminated information at step t. Sociability is a permanent property of the social system's participants; hence, the level of sociability can be supposed constant. As a rule, the relevance of information decreases over time; for each step, it is calculated using a special relevance decline coefficient and the forecasted information life cycle. However, according to practical evidence, an acute and significant problem retains its relevance in the information space for a long time in emergencies threatening the life and health of people.

Thus, the number of informed agents is given by [28]

$$K_{t+1} = K_t + q_t \left(\frac{N - K_t}{N} \right) \left(K_t^{++} + K_t^{--} \right) \bar{b} \,,$$

where N is the total size of the social system (the region's population). The coefficient $(N - K_t)/N$ reflects the share of uninformed participants at the previous step whereas K_t^{++} and K_t^{--} are the numbers of participants with pronounced attitudes (strongly positive and strongly negative, respectively).

Under the mass spread of infectious disease and the introduction of epidemic safety measures, it is interesting to forecast and study the spectrum of opinions at each information exchange step. The goal is to regulate social opinions by providing a correct understanding of the current epidemic situation and counteracting the dissemination of destabilizing and harmful information.

The distribution of opinions is described by the number of information exchange participants in each category from the set (2). The starting values $(K_0^{--}, K_0^{-}, K_0^{N}, K_0^{+}, K_0^{++})$ are determined within the initiating set L according to the given initial distribution of opinions.

The number of participants with strongly negative attitudes towards information at each step evolves as follows [28]:

$$K_{t+1}^{--} = K_t^{--} + \left(K_{t+1} - K_t \right) \Big[\nu_0^{--} - \nu_0^{--} \times \left(\omega^M + \omega^H \right) \times \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{-} \left(\omega^M + \omega^H \right) \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{N} \ \omega^H \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) \Big].$$

The factors $\dfrac{K_t^{++}}{K_t^{++} + K_t^{--}}$ and $\dfrac{K_t^{--}}{K_t^{++} + K_t^{--}}$ represent the shares of information exchange participants sharing strongly positive and strongly negative opinions, respectively. The formula clearly reflects how moderately and highly susceptible participants are influenced and change their opinions in a certain direction.

The number of participants with a strongly positive opinion is calculated by analogy [28]:

$$K_{t+1}^{++} = K_t^{++} + \left(K_{t+1} - K_t \right) \Big[\nu_0^{++} - \nu_0^{++} \times \left(\omega^M + \omega^H \right) \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{+} \left(\omega^{\mathrm{M}} + \omega^{\mathrm{H}} \right) \times \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{N} \ \omega^H \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) \Big].$$

The number of participants with a positive opinion is given by

$$K_{t+1}^{+} = K_t^{+} + \left(K_{t+1} - K_t \right) \Big[\nu_0^{+} - \nu_0^{+} \left(\omega^M + \omega^H \right) \times \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) - \nu_0^{+} \left(\omega^M + \omega^H \right) \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{++} \ \omega^M \left(\frac{K^{--}}{K^{++} + K^{--}} \right) + \nu_0^{-} \ \omega^H \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{N} \ \omega^M \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) \Big].$$

Finally, the number of participants with neutral attitude is calculated as

$$K_{t+1}^{N} = K_t^{N} + \left(K_{t+1} - K_t \right) \Big[\nu_0^{N} - \nu_0^{N} \left(\omega^M + \omega^H \right) + \nu_0^{-} \ \omega^M \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{+} \ \omega^M \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{++} \ \omega^H \left(\frac{K_t^{--}}{K_t^{++} + K_t^{--}} \right) + \nu_0^{--} \ \omega^H \left(\frac{K_t^{++}}{K_t^{++} + K_t^{--}} \right).$$

4. GENERAL PATTERNS OF INFORMATION INTERACTION: ANALYSIS AND APPLICATION IN CONTROL PROBLEMS

Figure 1 shows typical graphs obtained by computer simulations for the following model dataset:

▪ The social system is composed of 350 000 participants.

▪ The initiating set is 12%.

▪ The average number of links varies from 1 to 5 for 82% of participants and from 6 to 15 for 18% of participants.

▪ The initial distribution of opinions on the issue (the theme of the information disseminated) is specified by $\nu_0^{++} = 0.18$ (strongly positive), $\nu_0^{+} = 0.35$ (positive), $\nu_0^{N} = 0.2$ (neutral), $\nu_0^{-} = 0.17$ (negative), and $\nu_0^{--} = 0.1$ (strongly negative).

▪ The willingness to disseminate the information received is $q_0 = 0.3$.

▪ The levels of susceptibility are $\omega^L = 0.44$ (low), $\omega^M = 0.4$ (medium), and $\omega^H = 0.16$ (high).

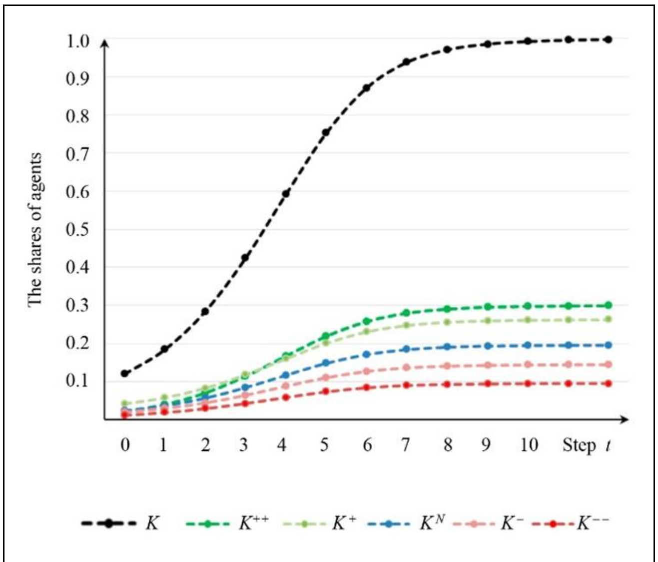

Fig. 1. The growing shares of informed participants and the distribution of their opinions.

According to the experiments, the growing shares of participants in each category represent a sigmoid, i.e., a smooth monotonically increasing nonlinear function with an *S*-shape. The growth is usually smooth. Sharp jumps in the shares of informed participants are possible only for very large (limit) levels of susceptibility and sociability; as surveys show, they are not typical for real social systems.

The proposed model can be used to assess information exchange dynamics under given conditions and forecast social opinions on different issues such as:

▪ the introduction of restrictive measures in a pandemic,

▪ possible shortages of medicines or protective equipment,

▪ the load on the healthcare system,

▪ vaccine development and application,

▪ decreased economic activities (trade, tourism, and culture),

▪ protests denying the danger of the virus and the need for epidemic safety measures.

The resulting forecast based on artificial data simulations can be assessed as unsatisfactory. In this case, the control problem is to choose a control action for the system that will change the level of awareness and the opinion distribution vector to the targets with minimum costs.

Control actions consist in varying the parameters of the social system, e.g., by selecting an appropriate information dissemination channel (i.e., the size of the initiating set) and adjusting the information block's content (i.e., the initial distribution of opinions on issues) or its format (i.e., the willingness to disseminate this block). Also, the formation and detailed planning of available control actions are in the competence of sociologists and psychologists specializing in susceptibility.

The population's reaction is forecasted to make justified managerial decisions and stabilize public sentiment. It is important to plan and disseminate complete and convincing information through trusted media channels for the population to realize the epidemical evolution properly.

The following actions can be performed to counteract the spread of destructive information and avoid destabilization: decreasing the level of susceptibility to destructive information (by reducing trust in its sources) or decreasing the willingness to disseminate it (the loss of relevance compared to other information resources).

Figure 2 shows information dissemination dynamics under the following corrections to the experimental data:

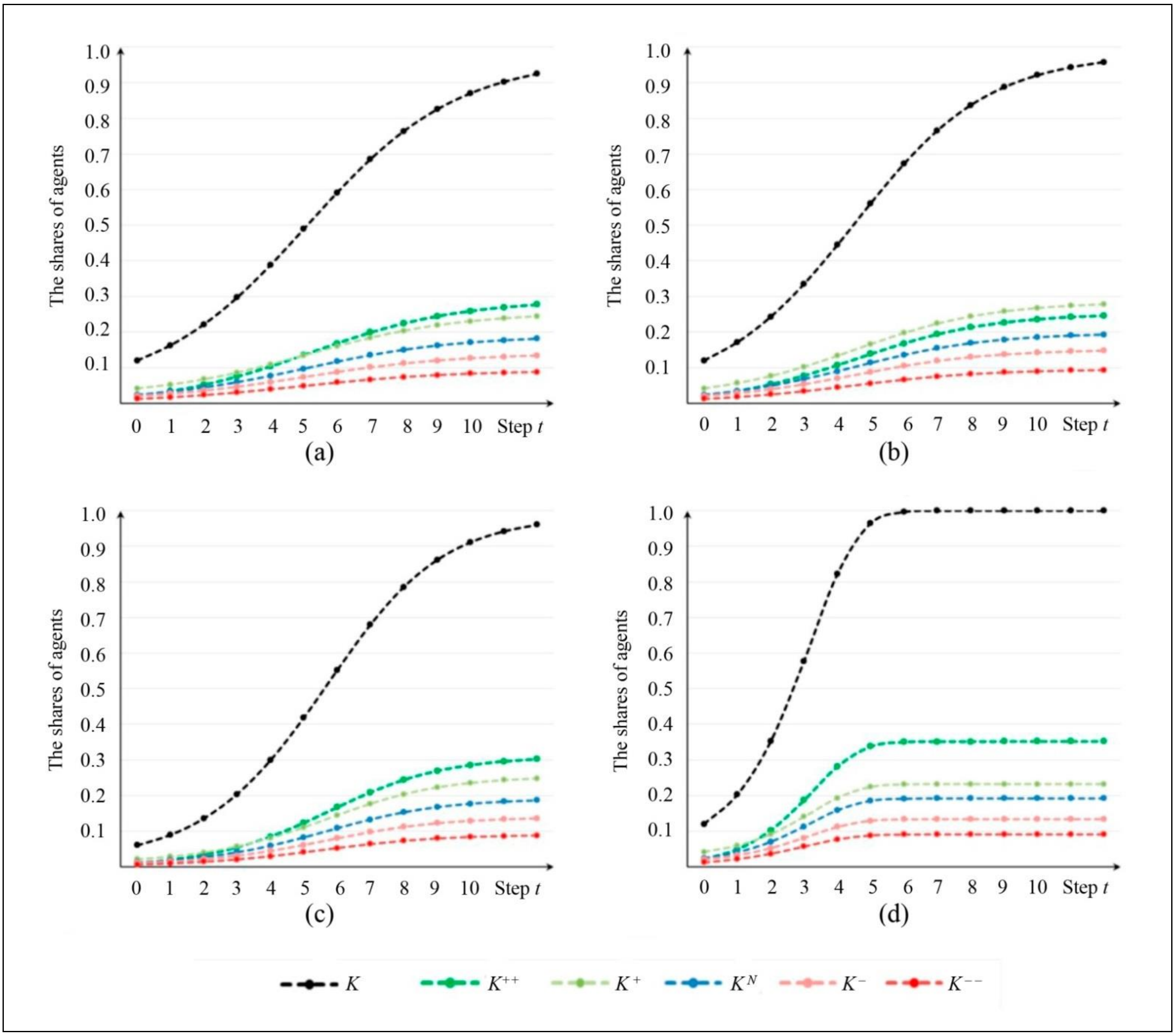

Fig. 2. Information dissemination dynamics under an intervention strategy.

a) decreasing the willingness to disseminate the information received: $q_0 = 0.2$;

b) decreasing the level of susceptibility: $\omega^L = 0.6$ (low), $\omega^M = 0.32$ (medium), and $\omega^H = 0.08$ (high);c) reducing the size of the initiating set: $L = 6\%$;

d) increasing the parameter values: $q_0 = 0.45$, $\omega^L = 0.24$, $\omega^M = 0.53$, and $\omega^H = 0.23$.

Compared to Fig. 1, the graphs in Figs. 2a–2c (Fig. 2d) show a decrease (an increase, respectively) in the speed of information dissemination over the social system.

Figure 3 presents an example with no opinion polarization on the issue and a predominantly neutral attitude at the time of launching the information block $\left(\nu_0^{++} = 0.08, \quad \nu_0^{+} = 0.14, \quad \nu_0^{N} = 0.61, \quad \nu_0^{-} = 0.12, \quad \nu_0^{--} = 0.05\right)$:

a) for the levels of susceptibility $\omega^L = 0.2$, $\omega^M = 0.6$, and $\omega^H = 0.2$;

b) for the decreased levels of susceptibility $\omega^L = 0.51$, $\omega^M = 0.42$, and $\omega^H = 0.07$.

The model demonstrates that in the numerical example under consideration, timely measures reducing the level of trust in the source affect the distribution of positive and negative opinions while maintaining an overall neutral information background.

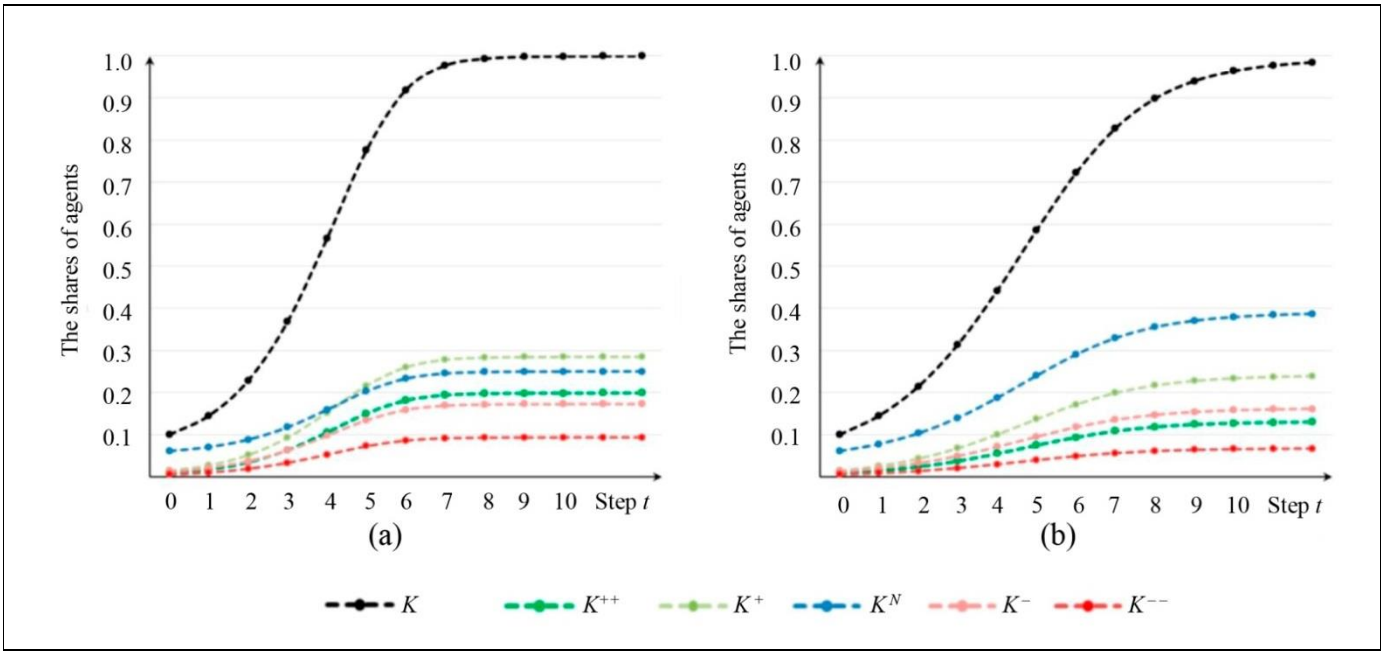

Fig. 3. The distribution of opinions under an intervention strategy.

CONCLUSIONS

Like any emergency, an epidemic generates many negative consequences, influencing almost all sides of human life and being a source of severe psychological stress.

In addition to purely medical aspects, social processes directly or indirectly affect the spread of the disease. Situation analysis and modeling from this point of view assist in organizing competent preventive and psychological corrective measures among the population, reducing the level of stress, and stabilizing social relations.

The mathematical model considered in this paper can be used to forecast the dynamics of social opinions on the applied measures of epidemic safety and to develop managerial decisions toward the adoption of these measures by the population. A numerical example of the distribution of opinions under given characteristics of the social system has been provided; the possibility of changing the dynamics of information dissemination by an intervention strategy has been demonstrated.

In simulation experiments, it is of interest to study several organizational aspects of social systems as follows: clustering of the interaction network of participants and the probability of localization of disseminated information in one cluster; the motivation of participants, incentives, and restrictions in information dissemination; the total susceptibility threshold of a participant simultaneously subjected to several information blocks and sources (as a result, the participant may neglect some of them and not react to the control action). Also, it is necessary to analyze real data from online social media. Further research in these directions seems topical and promising.

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