Epidemiological Informing of the Population in Cities: Models and Their Application

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Abstract

With an increase in population density and contacts between people and the emergence of new biological viruses, the threat of various epidemics is growing. Countering these threats involves the implementation of large-scale preventive, therapeutic, and other measures, both before the start of and during the epidemic. Epidemiological informing of the population plays an important role in such counteraction. The currently used models of sharing epidemiological information of the population of cities largely do not meet the needs of practice. This negatively affects the effectiveness of the response to epidemics. The purpose of the study is to develop new models and justify their applicability for understanding the processes in public health, the impact of epidemics on the economy and business. For the quantitative substantiation of epidemiological information spreading programs (scenarios), a method based on new models of epidemic development in related cities is proposed. The method is characterized by a new target function that links economic efficiency with the state of health of the population in an epidemic. The models differ from the known solutions both in the space of the selected states of the processes under study and in the connections between them.

Using the developed method, seven possible programs of sharing epidemiological information with the population of related cities were analyzed and the best of them werefound for specific conditions. New regularities have been established between the parameters of the programs being implemented and the results of the impact on the health and performance capability of the population. It is shown that an epidemic can develop in cities that are differently connected to one another by vehicles. The proposed method allows for quicklying the best epidemiological information sharing programs for the population. The models underlying this method make it possible to predict public health and the impact of epidemics on the economy and businesses, depending on the planned measures to counteract epidemics. They are also applicable for determining the sources and time of an infection's onset. The obtained simulation results are in good agreement with the known facts. The method can be applied in advanced information systems to support the adoption of far-sighted decisions to counteract epidemics.

Keywords:
epidemiological informing; programmes; forecasting; health; economic losses; epidemic development models

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Introduction

A key aspect of forecasting public health and assessing the impact of epidemics on the economy and businesses, is the sharing of epidemiological information with the population in cities connected by large passenger flows (further on referred to as "connected cities"). The success of a comprehensive response to epidemics largely depends upon the effectiveness of such information programs and underlying models and approaches which allow one to build alternative scenarios (Papa et al., 2020; Abdulai et al., 2021).

General issues of informing people about possible threats to life and health have been studied in sufficient detail (Liu et al., 2020; Lukyanovich, Aflyatunov, 2015). Attempts have been made to assess the impact of information sources on people's situational awareness and social distancing (Wu et al., 2012; Qazi et al., 2020; Tiwari et al., 2021), including in the context of media coverage of the COVID-19 pandemic and early proliferation of the infection in China (Liu et al., 2020; Zhou et al., 2020). A number of models exist, each with its own advantages and disadvantages under particular conditions (Chubb, Jacobsen, 2009; Nadella et al., 2020), which help predict the development of epidemics (Newbold, Granger, 1974; Holko et al., 2016; Holko et al., 2020; Hu et al., 2020; Levashkin et al., 2021; Medrek, Pastuszak, 2021; Katris, 2021; Osipov et al., 2021).[1] Various approaches are applied to monitor the situation and process statistical data in order to set parameters and initial states for the application of these models, but little attention is paid to assessing the potential impact of sharing epidemiological information on public health. Methods for assessing the associated potential economic risks are also insufficiently developed. The imperfection of existing approaches makes it difficult to develop effective programs to inform the public about epidemics, which negatively affects the response to them.

The proposed new method of substantiating epidemiological information programs (scenarios) for the population of connected cities, and the associated models are designed to more effectively respond to pandemics by taking into account the informational aspect of their development and economic losses. Such models will help one to more accurately assess the efforts to counter epidemics through the prism of information policy and population response, which affect the natural dynamics of disease proliferation.

Materials and Methods

Method

Epidemiological information programs are based on the analysis of public health, economic and business data, features of the epidemic specific to connected cities, and possible response measures. Such information sharing is conducted regularly, according to the prevailing conditions. The program design, which should take into account potential effects on public health and the economic costs, should be aimed at developing an optimal epidemiological information program. Based on the evaluation results, programs that do not meet the requirements are excluded, and alternative ones are presented for consideration. Then all programs meeting acceptable public health criteria are evaluated in terms of economic indicators to select the most efficient ones. When the optimal program is identified, it is translated into specific actions. The substantiated program is communicated to the public via media in the form of instructions to overcome the epidemic.

Thus, the objective is to design an epidemiological information program (PRG_o) whose implementation would create the highest economic effect ($W_o(PRG_o, \Delta T)$) during the given time interval ΔT, which would meet the relevant public health and implementation cost requirements.

The effects ($W_s(PRG_s, \Delta T)$ of implementing program PRG_s during the interval $\Delta T = T_K - T_0$ can be defined as follows:

$$W_s(PRG_s, \Delta T) = \sum_{k=0}^{K} \int_{T_k}^{T_{k+1}} \sum_{i=1}^{L} V_{ki}(PRG_s, \Delta T_k) \cdot P_{ki}(PRG_s, T_k \leq t < T_{k+1})\, dt,$$

where

$V_{ki}(PRG_s, \Delta T_k) = V_{io}/(1 + \Delta t_{ki}(I_{ks} \in PRG_s)/\tau)$ is the economic performance of the population per unit of time in the i-th state during the k-th interval $\Delta T_k = T_{K+1} - T_k$ of the implementation of the s-th epidemiological information program;

V_{io} is the average economic performance of the population in the i-th state without the restrictive measures;

τ is the time interval for estimating V_{io};

$\Delta t_{ki}(I_{ks} \in PRG_s)$ is the additional time needed to achieve the same result when restrictive measures are in place;

I_{ks} are the elements of program PRG_s implemented during the k-th interval.

[1] See also: https://docs.idmod.org/projects/emod-environmental/en/latest/model-seir.html, accessed 22.01.2022.

P_{ki} $(PRG_s,\ T_k \le t < T_{k+1})$ is the probability that the population would be in the i state during the k-th interval of implementation of the s-th epidemiological information program.

The desired program $PRG_s = PRG_s\ (I_{ks};\ k = 0.1,\ \dots,\ K)$ may comprise K information blocks I_{ks}, and must belong in the set of effective programs which meet the given requirements.

The algorithm for solving this problem comprises the following steps:

1. Assessing the initial state of public health, the current dynamics of the epidemic, the employment in manufacturing and service sector, and the scope for informing the public.
2. Designing effective epidemiological information programs meeting the specified requirements.
3. Assessing each program's impact upon the resulting performance indicator and identifying the optimal one.

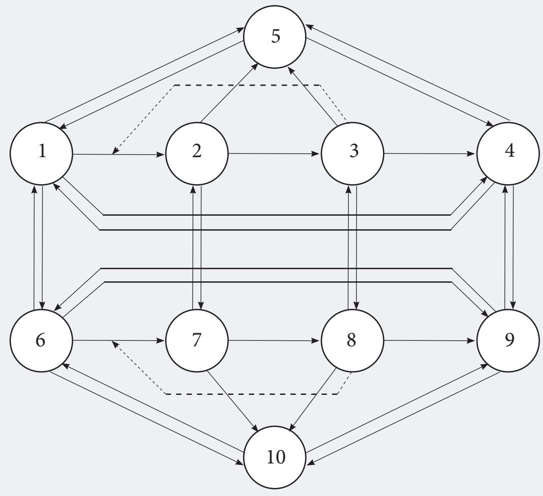
For the purposes of this assessment, the impact of PRG_s programs on the development model parameters and the course of the epidemic must be determined for each considered time interval. Then with the help of this model and taking into account its initial states, probabilities P_{ki} $(PRG_s,\ t)$ can be estimated. Knowing these probabilities and $V_{ki}(PRG_s,t)$, it is possible to estimate the damage prevented over the relevant time interval. $V_{ki}(PRG_s,t)$ values can significantly vary for different population states and strongly depend upon PRG_s parameters. To estimate the damage prevented during the next $k + 1$ time interval, the previous calculation of P_{ki} $(PRG_s,\ t)$ should be taken into account.

Epidemic Development Models in Connected Cities

New models that take into account an extended range of possible factors affecting epidemiological development are suggested to determine P_{ki} $(PRG_s,\ t)$. One of them is a state graph of epidemiological development in two connected cities (Figure 1). The graph vertices in Figure 1 corresponds to the population states of the first (1-5) and second (6-10) cities. The arcs in the graph presented in Figure 1 reflect the transitions of the epidemic from one state to another. These transitions are described in Table. 1. This model is different from known solutions (Browne et al., 2015) primarily due to its taking into account additional important correlations.

In line with the probability theory limit theorem for event flows, the graph in Figure 1 can correspond to a system of 10 differential equations relating the probabilities of the selected states (Box 1). Rates of transition from one state to another λ_{ij} serve as these equations' parameters, which depend upon the characteristics of the implemented

Figure 1. **State graph of epidemic development in two connected cities**



Note: vertices 1, 6 - healthy population susceptible to the infection; 2, 7 - infected population displaying no symptoms (infection carriers); 3, 8 - infected population with symptoms; 4, 9 — healthy population with immunity; 5, 10 - dead population. Each state is associated with the relative number of people in that state. Normalisation is performed in relation to the entire population of both cities.

Source: authors.

epidemiological information programs. This dependence is manifested in the form of negative and positive adjustments of λ_{ij} reflecting the change in the nature of transitions between the model states corresponding to each control action.

As a result of communicating epidemiological information to the population of the first city in the scope of the program being implemented, the parameters of transitions 1→2, 3→4, 1→6, 2→7, 3→8, and 4→9 may change. For the second city, the same applies to transitions 6→7, 8→9, 6→1, 7→2, 8→3, and 9→4.

The epidemic development can be scaled up to cover multiple cities (or countries) simultaneously, by enlarging the states presented in Figure 1. For example, states 2, 3 and 1, 5 can be combined, since new births compensate for population decline. State 4 remains unchanged. Thus, the epidemiological model of each individual city in a generalized form can be formalized by three related population states. By combining individual city models on the basis of the population's infection state, higher-level epidemic development models can be developed (Figure 2).

The models presented in Figures 2a and 2b can be incorporated in differential equation systems to analyze the process dynamics relative to the initial

Box 1. **Differential equations of the model**

$$\begin{cases}
\frac{dP_1(t)}{dt} = \lambda_{51}P_5(t) + \lambda_{61}P_6(t) - (\lambda_{12}P_3(t) + \lambda_{16} + \lambda_{15} + \lambda_{14})P_1(t) + \lambda_{41}P_4(t) \\
\frac{dP_2(t)}{dt} = \lambda_{12}P_3(t)P_1(t) + \lambda_{72}P_7(t) - (\lambda_{23} + \lambda_{25} + \lambda_{27})P_2(t) \\
\frac{dP_3(t)}{dt} = \lambda_{23}P_2(t) + \lambda_{83}P_8(t) - (\lambda_{34} + \lambda_{35} + \lambda_{38})P_3(t) \\
\frac{dP_4(t)}{dt} = \lambda_{14}P_1(t) + \lambda_{34}P_3(t) + \lambda_{94}P_9(t) - (\lambda_{45} + \lambda_{49} + \lambda_{41})P_4(t) + \lambda_{54}P_5(t) \\
\frac{dP_5(t)}{dt} = \lambda_{15}P_1(t) + \lambda_{25}P_2(t) + \lambda_{35}P_3(t) + \lambda_{45}P_4(t) - \lambda_{51}P_5(t) - \lambda_{54}P_5(t) \\
\frac{dP_6(t)}{dt} = \lambda_{16}P_1(t) + \lambda_{10,6}P_{10}(t) - \left(\lambda_{67}P_8(t) + \lambda_{61} + \lambda_{6,10} + \lambda_{69}\right)P_6(t) + \lambda_{96}P_9(t) \\
\frac{dP_7(t)}{dt} = \lambda_{67}P_8(t)P_6(t) + \lambda_{27}P_2(t) - \left(\lambda_{72} + \lambda_{78} + \lambda_{7,10}\right)P_7(t) \\
\frac{dP_8(t)}{dt} = \lambda_{78}P_7(t) + \lambda_{38}P_3(t) - \left(\lambda_{83} + \lambda_{89} + \lambda_{8,10}\right)P_8(t) \\
\frac{dP_9(t)}{dt} = \lambda_{69}P_6(t) + \lambda_{89}P_8(t) + \lambda_{49}P_4(t) - \left(\lambda_{94} + \lambda_{9,10} + \lambda_{96}\right)P_9(t) + \lambda_{10,9}P_{10}(t) \\
\frac{dP_{10}(t)}{dt} = \lambda_{6,10}P_6(t) + \lambda_{7,10}P_7(t) + \lambda_{8,10}P_8(t) + \lambda_{9,10}P_9(t) - \lambda_{10,6}P_{10}(t) - \lambda_{10,9}P_{10}(t)
\end{cases}$$

Source: authors.

states. Such models allow for predicting epidemic proliferation across multiple cities depending on the epidemiological information programs implemented there. Forecasting of this kind requires data on the model parameters and on the initial process states determined by the probabilities $P_i(t = 0)$ that at the time $t = 0$, the process would be in the i-th states. Since the period of time is divided into intervals, the relevant times are $T_k = 0$. Each of the probabilities $P_i(t = 0)$ can be defined as the relative number of people in the i-th state at a given time.

Since model parameters such as rate of transition from one state to another λ_{ij} depend on epidemic response measures, the impact of the epidemiological information program PRG_s on changes in λ_{ij} can be estimated according to the rule:

$$\lambda_{ij} = \lambda_{ij}^{*} \pm \beta_{ij} g_{ij} (PRG_s),$$

where

β_{ij} is the maximum possible change in the transition rate ij depending on the epidemic response measures taken;

g_{ij} (PRG_s) is the probability that the implementation of the PRG_s program will achieve changes in λ_{ij} equal to β_{ij}.

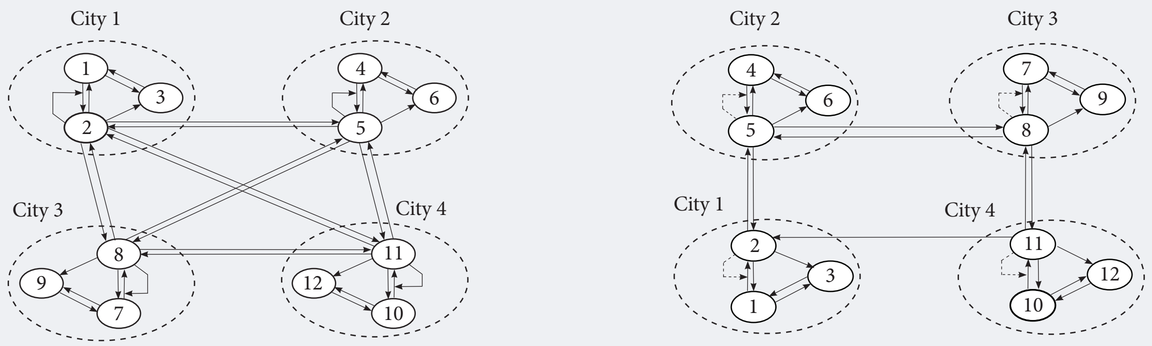
Thus, knowing the initial process states and the parameters of the applied model allows one, by resolving the corresponding system of differential

Table 1. **Transitions of the epidemic from one state to another**

Transitions	Description
1→2, 6→7	Healthy population vulnerable to the infection (states 1, 6) over time can move on to states 2, 7 (asymptomatic disease). The transition rate depends on the probabilities of states 3, 8. This dependence is shown in Fig. 1 by dash-dotted arrows.
2→3, 7→8	Infected population of the cities displaying no symptoms (states 2, 7) move on to states 3, 8 - infected population with symptoms of the disease.
3→4, 8→9	After treatment, infected population with symptoms (states 3, 8) move on to states 4, 9 - healthy population with immunity.
1→4, 6→9	After vaccination, healthy population vulnerable to the infection (states 1, 6) move on to states 4, 9.
4→1, 9→6	After losing the immunity, population of the cities in states 4, 9, return to states 1, 6.
1→6, 6→1, 2→7, 7→2, 3→8, 8→3, 4→9, 9→4	Transitions caused by people's travelling between the cities using different modes of transport.
1→5, 2→5, 3→5, 4→5, 6→10, 7→10, 8→10, 9→10	Transitions caused by mortality.
5→1, 4→4, 10→6, 10→9	Transitions caused by births.
Source: authors.	

Figure 2. **Epidemic development models in connected cities**

a) epidemic development in fully connected cities ***b) sequential cyclic proliferation of the epidemic***



Note: selected population states in individual cities are shown by dotted circles; 1, 4, 7, 10 - healthy population vulnerable to infection; 2, 5, 8, 11 - infected population; 3, 6, 9, 12 - healthy population with immunity. Transitions 3→1, 6→4, 9→7, 12→10 primarily depend on the duration of immunity. When it disappears, the population moves from states 3, 6, 9, 12 to states 1, 4, 7, and 10.

Source: authors.

equations using known methods, to achieve predictive probabilities P_{ki} $(PRG_s, T_k \leq t < T_{k+1}) = P_{ki}$ $(\lambda_{ij}^* \pm \beta_{ij}\, g_{ij}\, (PRG_s), T_k \leq t < T_{k+1})$ that the population would be in the i-th state during the k-th time interval if the s-th epidemiological information program is implemented. Given these probabilities, it becomes feasible to forecast the economic effects W_s $(PRG_s, \Delta T)$ of implementing programs (PRG_s) over the interval $\Delta T = T_K - T_0$.

Based on the simulation results, morbidity proliferation in cities over time can be estimated. Changing the initial model conditions and implementing various administrative measures in the scope of PRG_s allow one to build alternative epidemic development scenarios and predict the programs' impact upon public health and the economy. A particular benefit of the described models (Figures 2a and 2b) may be associated with the ability to identify the place and time of the onset of the infection, i.e., to conduct a reverse analysis of the epidemic development in connected cities.

Initial Data

The statistics of COVID-19 proliferation in Russian regions and federal-level cities (Table 2) for the period from March 6 to December 30, 2020 was used as the initial data for modeling the impact of epidemiological information programs. To analyze the impact of epidemiological information sharing of the population with the system of equations presented in Figure 2, the values given in Table 3 were applied as initial transition rates. Average values of population performance in the i-th state with no restrictive measures in place were set in relative units, based on known examples (Bellman, 1983): (1; 0.75; 0.3; 1; 0; 0; 0; 0; 0; 0).

Results and Discussion

Problems (1) - (5) were solved using the MatLab software package. To begin with, let us consider the example of the interaction between two cities with a heavy passenger flow in both directions, in which, despite the different population size, similar epidemiological information programs are being implemented along with typical "safe period" preventive measures. In one of the cities, an infection source emerges and the epidemic begins to spread. How quickly will the situation develop in the first and second cities if epidemiological information sharing with the public is not adjusted?

To answer this question, the epidemic's development was modeled for a period of 150 weeks (Figure 3). The initial states in the equations system of the model presented in Figure 2 were set as (0.39888; 0.001; 0.00; 0.00; 0.00; 0.00012; 0.59982; 0.0; 0.0; 0.0; 0.0; 0.00018). Table 3 was used to set the transition rate values. Figure 3a shows the change in the relative number of healthy people

Table 2. **Online resources for monitoring the proliferation of COVID-19 pandemic**

Name	URL
An interactive web-based dashboard to track COVID-19 in real time.	https://www.thelancet.com/journals/laninf/article/PIIS1473-3099(20)30120-1/fulltext, accessed 20.01.2022.
Our World in Data. Coronavirus Pandemic (COVID-19)	https://ourworldindata.org/coronavirus, accessed 20.01.2022.
Online COVID-19 Coronavirus Map	https://coronavirus-monitor.info/, accessed 20.01.2022.

Source: authors.

Table 3. **Initial transition rates**

Transitions	Transition rates	Transitions	Transition rates
1→2	$0.750 \cdot P_3(t)$	9→6	0.0007
6→7	$0.750 \cdot P_8(t)$	4→5	0.000235
1→4	0.0007	9→10	
6→9		5→1	0.39
2→3	0.21	10→6	
7→8		5→4	0.39
3→4	0.1	10→9	
8→9		1→6	0.00084
1→5	0.000235	6→1	0.00056
6→10		2→7	0.00084
2→5	0.000235	7→2	0.00056
7→10		3→8	0.00084
3→5	0.0011	8→3	0.00056
8→10		4→9	0.00084
4→1	0.0007	9→4	0.00056

Source: authors.

vulnerable to the infection in the first and second cities over time. Figure 3b, 3c, 3d, and 3e show the probabilities that the populations of the two cities are in states 2, 7 (infected, no symptoms); 3, 8 (infected with symptoms); 4, 9 (healthy with immunity); and 5, 10 (dead). Figure 3f presents the dependencies and the economic performance of the population in the analyzed cities when the initial epidemiological information program is implemented:

$$V_{\Sigma 1}(PRG_s, t) = \sum_{i \in 1,2,3,4} V_i(PRG_s, t) \cdot P_i(PRG_s, t)\ ,$$

$$V_{\Sigma 2}(PRG_s, t) = \sum_{i \in 6,7,8,9} V_i(PRG_s, t) \cdot P_i(PRG_s, t).$$

The expected total economic effect $W_Z\,(PRG_s,\ \Delta T)$ for the case under consideration during a 150-week interval was 143.5 conventional economic units (CEU), of which 57.5 CEU fell to the first city, and 86.0 CEU to the second one.

As shown in Figure 3, over time the number of healthy people vulnerable to the infection rapidly declines, while the number of infected people increases. However, in the first city, the highest number of infected people with symptoms falls in the 70th week, and in the second in the 80th. In the second city, infection is transmitted by people crossing the border between the cities by air, land, and water. Relative mortality in the second city peaks at 0.00036, which is 1.94 times higher than the initial one. With the input data used, the largest economic downturn occurs in week 80.

Note that at the time $t = 0$, the number of infected in the first city amounted to 0.1% of the total population of both cities. The number of infected with symptoms in this city peaked only after 14 months, while in the second city it happened after 16.5 months.

The overall impact of the epidemiological information program under consideration (*PRG1*) on the health and economic indicators of the population in connected cities is presented in Table 4. The table also shows the estimated effect of alternative epidemiological information programs designated PRG 2–7. Brief descriptions of these programs (without specific effects on model parameters) are given in Table 5.

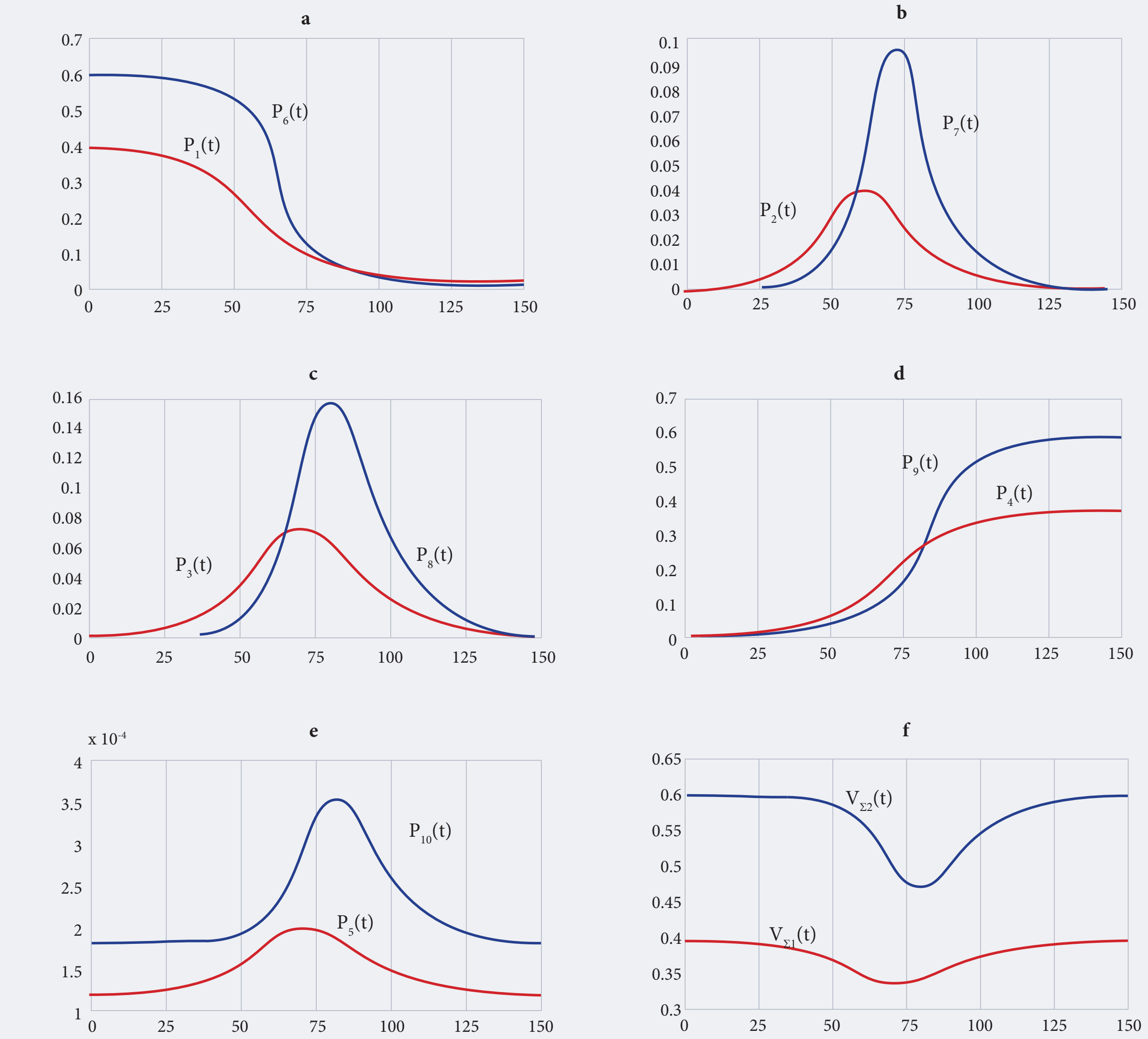
When, in contrast to *PRG1*, the *PRG2* program informs the population of the first city about the need to wear protective masks and maintain social distance, the rate of the transition 1 → 2 in the model decreases. At the same time additional time costs $\Delta t_{ki}\ (I_{ks(Z)} \in PRG_{s(Z)})$ arise, which in the example under consideration amount to 0.1 of τ. *PRG3* differs from *PRG2* in that similar protective measures are taken in the first and second cities simultaneously. If protective measures are taken only in the first city (*PRG2*), the total economic effect amounts to 138.8 CEU, but when such measures are implemented in the two cities at the same time (*PRG3*), it amounts to 131.5 CEU. According to these estimates, economic performance compared to *PRG1* declines, while peak infection rates in both cities shift to the right and decrease, along with mortality. If the implemented programs provide for vaccination (*PRG4,5*), in the first (*PRG4*) or in both cities (*PRG5*), the simulation results suggest higher values of public health indicators can be achieved during the epidemic along with higher productivity.

If epidemiological information sharing programs limit the links between the cities, infection rates differ from the above examples. *PRG6* provides for informing the public about restrictions on travel between the first and second cities starting from week 50. According to *PRG7*, people are informed about the restrictions (and the latter are introduced) starting from the time $t = 0$. An analysis of Table 5 shows that introducing these measures with a shift of 50 weeks does not lead to any appreciable results. A significant effect in the form of morbidity peaks shifting to the right is observed only when restrictions are introduced from the time $t = 0$.

Modeling the impact of epidemiological information programs on the economic performance of the population suggested that *PRG5* was the best one: the effect of its implementation to inform the population of both cities about the need for vaccination was 149.3 CEU. *PRG7* (which provided for severe restrictions on travel) was the least effective in this regard.

Let us consider the features of the epidemic's development in four cities (Figure 2a) taking into

Figure 3. Epidemic development in connected cities if no additional epidemiological informing measures are taken



Source: authors.

account the response measures. According to the model, population in each city can be in three states: 1, 4, 7, 10 (healthy population vulnerable to the infection); 2, 5, 8, 11 (infected population); and 3, 6, 9, 12 (recovered population). Let us assume immunity after recovery or vaccination will last for two years. The infection originated in the first city. The population distribution by city is (0.3, 0.2, 0.2, 0.3). The conditions for countering the pandemic through epidemiological information sharing with the public in the first, third, and fourth cities are the same. In the second city, the possibilities of treating the sick are more limited. The results of modeling the development of the epidemic using this model are shown in Figure 4.

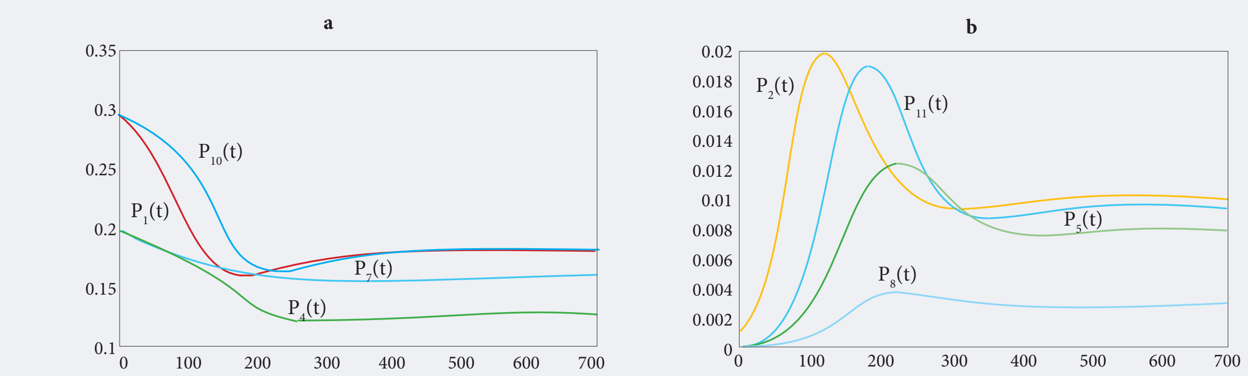
Figure 4a shows the time dependencies of the probability that cities are in states 1, 4, 7, 10 (healthy population vulnerable to the infection). Similar dependencies for states 2, 5, 8, 11 (infected population) are shown in Figure 4b. If the epidemic develops this way, and the population have limited immunity, pronounced waves can be observed during a 700-week interval (see Figures 4a and 4b). An analysis of Figure 4 reveals that without special measures, the infection can persist in the cities for many years. The duration depends upon the structure of passenger flows, the distance between the cities, population density, the epidemiological response measures implemented, virus mutations, weakening of immunity over time, and so on. Since

Table 4. Impact of epidemiological information programmes on health and economic performance of population in two connected cities

Epidemiological informing programme	City 1			City 2			Cities1, 2
	$P_3(t^*)$ / t^*	$P_5(t^*)$ / t^*	$V_{\Sigma1}(0)/V_{\Sigma1}(t^*)$ / t^*	$P_8(t^*)$ / t^*	$P_{10}(t^*)$ / t^*	$V_{\Sigma2}(0)/V_{\Sigma2}(t^*)$ / t^*	$W_s(PRG_s, \Delta T)$
PRG 1	0.073 / 70	2.00×10^{-4} / 70	0.40/0.34 / 70	0.158 / 80	3.60×10^{-4} / 80	0.60/0.47 / 80	143.5
PRG 2	0.044 / 94	1.70×10^{-4} / 94	0.37/0.33 / 94	0.158 / 83	3.50×10^{-4} / 83	0.60/0.47 / 83	138.8
PRG 3	0.040 / 96	1.65×10^{-4} / 96	0.37/0.33 / 96	0.114 / 105	3.05×10^{-4} / 105	0.55/0.46 / 105	131.5
PRG 4	0.015 / 70	1.35×10^{-4} / 70	0.40/0.38 / 70	0.15 / 82	3.50×10^{-4} / 82	0.60/0.47 / 80	145.6
PRG 5	0.0142 / 70	1.35×10^{-4} / 70	0.40/0.38 / 70	0.0155 / 100	1.98×10^{-4} / 100	0.60/0.58 / 100	149.3
PRG 6	0.073 / 70	2.00×10^{-4} / 70	0.40/0.34 / 70	0.0156 / 80	3.50×10^{-4} / 80	3.50×10^{-4} / 80	131.5
PRG 7	0.073 / 70	2.00×10^{-4} / 70	0.40/0.34 / 70	0.0156 / 95	3.50×10^{-4} / 95	0.60/0.45 / 95	130.6

Source: authors.

Figure 4. Assessment of epidemic development in connected cities using the model in Fig. 3a



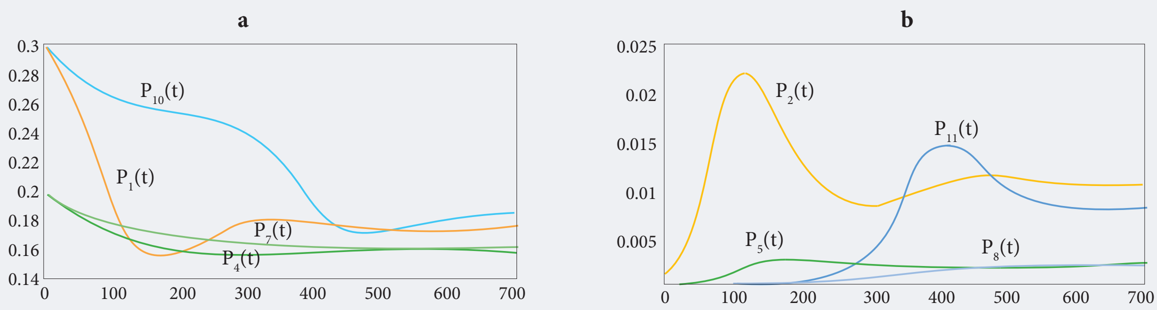
Source: authors.

Table 5. Alternative epidemiological information programmes

Programme code	Description
PRG1	Ongoing (basic) programme to inform the public, not really tailored to the actual epidemic specifics.
PRG2	Additional programme to further inform the population of the first city about the need to wear protective masks and maintain social distance. The second city is informed in the usual way.
PRG3	A programme to inform the population of both cities about the need to wear protective masks and maintain social distance.
PRG4	A programme to inform the population of the first city about the need for vaccination.
PRG5	A programme to inform the population of both cities about the need for vaccination.
PRG6	Awareness programme on restrictions on travel between the first and second cities starting from week 50.
PRG7	A programme to inform the population about the restrictions on travel between the first and second cities starting from time t = 0.

Source: authors.

Figure 5. Assessment of epidemic development in connected cities using the model in Fig. 3b



Source: authors.

the pace of epidemiological development in large cities is much higher than in small towns, this alone can create wave patterns.

When additional epidemiological measures are implemented, the model in Figure 2a can be changed as shown in Figure 2b, where the infection proliferates sequentially from the first to the fourth city and then returns to the first one. Simulation results (Figure 5) for this model are more undulatory than those in Figure 4. Following the epidemic response measures, the incidence rates in the second, third, and fourth cities (Figure 5b) decreased compared with Figure 4b, while the incidence peaks significantly shifted over time.

Table **6. Period of time 1% infection rate was achieved in selected Russian regions**

Cities and regions	Date in 2020
Moscow	14 May
Murmansk	13 July
Nizhny Novgorod	26 September
Khabarovsk region	11 October
St. Petersburg	21 October
Voronezh region	26 October
Krasnoyarsk region	5 November
Primorsky region	15 November
Sverdlovsk region	20 November
Rostov region	5 December
Novosibirsk	30 December
Chelyabinsk region	30 December

Source: authors.

To compare the modeling results with the existing statistical data (see Table 2), Table 6 was compiled showing the dates when a number of Russian regions reached the 1% COVID-19 infection rate. An analysis of this data shows that the obtained simulation results do not contradict the available statistics.

Conclusion

This study presents a method for quantifying epidemiological information programs in connected cities and new epidemic development and response models. New correlations have been revealed between the indicators describing public information programs, the state of public health, and economic performance. The results obtained allow one to confirm a strong correlation between the three above elements. The economic costs of epidemics that can be taken into account in forecasting include the costs of medical and preventive measures, informing the public about epidemic response, temporary disability compensation, etc.

The proposed method helps one find evidence-based epidemiological response solutions by estimating the effectiveness of planned measures. The developed models can be applied to assess current and future waves of epidemics, and their impact upon the economy and businesses. The models the presented method is based upon are also suitable for determining the location and time of the onset of an infection. The method is applicable to advanced epidemiological policy decision support information systems.

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