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ON COVID-19 EPIDEMIC PROCESS SIMULATION: THREE REGRESSION APPROACHES INVESTIGATIONS

*An outbreak of a new coronavirus infection was first recorded in Wuhan, China, in December 2019. On January 30, 2020, the World Health Organization declared the outbreak a Public Health Emergency of International Concern and on March 11, it a pandemic. As of January 2022, over 340 million cases have been reported worldwide; more than 5.5 million deaths have been confirmed, making the COVID-19 pandemic one of the deadliest in history. The digitalization of all spheres of society makes it possible to use mathematical and simulation modeling to study the development of the virus. Building adequate models of the epidemic process will make it possible not only to predict its dynamics but also to conduct experimental studies to identify factors affecting the development of a pandemic, determine the behavior of the virus in certain areas, assess the effectiveness of measures aimed at stopping the spread of infection, as well as assess the resources needed to counter the epidemic growth of the disease. This study aims to develop three regression models of the COVID-19 epidemic process in given territories and to investigate the experimental results of the simulation. The research is **targeted** at the COVID-19 epidemic process. The research **subjects** are methods and models of epidemic process simulation, which include machine learning methods, particularly linear regression, Ridge regression, and Lasso regression. To achieve the research aim, we have used forecasting **methods** and have built the COVID-19 epidemic process and regression models. As a **result** of experiments with the developed model, the predictive dynamics of the epidemic process of COVID-19 in Ukraine, Germany, Japan, and South Korea for 3, 7, 10, 14, 21, and 30 days were obtained. The authorities making decisions on the implementation of anti-epidemic measures can use such predictions to solve the problems of operational analysis of the epidemic situation, an analysis of the effectiveness of already implemented anti-epidemic measures, medium-term planning of resources needed to combat the pandemic, etc. **Conclusions.** This paper describes experimental research on implementing three regression models of the COVID-19 epidemic process. These are models of linear regression, Ridge regression, and Lasso regression. COVID-19 daily new cases statistics were verified by these models for Ukraine, Germany, Japan, and South Korea, provided by the Johns Hopkins Coronavirus Resource Center. All built models have sufficient accuracy to make decisions on the implementation of anti-epidemic measures to combat the COVID-19 pandemic in the selected area. Depending on the forecast period, regression models can be used to solve different Public Health tasks.*

Keywords: *epidemic model; the epidemic process; epidemic simulation; simulation; COVID-19; Ridge regression, Lasso regression, linear regression.*

Introduction

An outbreak of a new coronavirus infection was first recorded in Wuhan, China, in December 2019. On January 30, 2020, the World Health Organization declared the outbreak a Public Health Emergency of International Concern and on March 11 a pandemic [1]. As of January 2022, over 340 million cases have been reported worldwide; More than 5.5 million deaths have been confirmed, making the COVID-19 pandemic one of the deadliest in history [2].

The first coronaviruses, representatives of the Coronaviridae family from the order Nidovirales, were discovered in the first half of the last century. The first human coronavirus, HCoV-B814, was isolated in 1965 and has not survived to date [3]. By the beginning of the 21st century, coronaviruses were a severe veterinary problem, but it was believed that epidemic coronaviruses were not among the most dangerous for humans. These views have been revised. First, in 2002, the Severe acute respiratory syndrome-related coronavirus (SARS-CoV) virus entered the human bat population in Southeast Asia [4]. And then in 2012, when natural foci of the Middle East respiratory syndrome-related coronavirus (MERS-CoV) virus were discovered in the Arabian Peninsula [5].

At the end of November 2019, an outbreak of respiratory disease, later called COVID-19 (from the English Coronavirus infectious disease), caused by a third, previously unknown coronavirus, was registered in Wuhan (Hubei Province, China). Genetic studies have shown that the etiological agent of COVID-19 is closely related to SARS CoV (2002–2003) and belongs to the same species Severe acute respiratory syndrome-related coronavirus of the genus Betacoronavirus. In this regard, the virus was named SARS-CoV-2 [6].

The exponential spread of the new coronavirus, named COVID-19, is facilitated by a globalized interconnectedness of existing mobility systems, the same transit routes, and modes of transport used in international migration [7]. This distinguishes the current pandemic from previous ones and has contributed to the rapid spread of the virus worldwide.

COVID-19 has had an unprecedented impact on communities around the world [8]. Over the past two years, many problems have emerged with a wide range of medical, economic, and social impacts, directly or indirectly caused by the virus or exacerbated by the pandemic. Many millions of people have lost their jobs and others have faced the closure of their businesses as entire manufacturing sectors have been forced to shut down [9].

The global pandemic has also affected the digitalization of many areas of life: from the economy [10] to medicine [11]. Many interactive online information dashboards have emerged to enable health authorities, researchers, and the general public to visualize and track the COVID-19 outbreak as it develops [12]. These dashboards show the number of confirmed COVID-19 cases, deaths, and recoveries at the country level and how the number of cases has changed over time.

This is what makes it possible to use mathematical and simulation modeling to study the development of the virus. Building adequate models of the epidemic process will make it possible not only to predict its dynamics but also to conduct experimental studies to identify factors affecting the development of a pandemic, determine the behavior of the virus in certain areas, assess the effectiveness of measures aimed at stopping the spread of infection, as well as assess the resources needed to counter the epidemic growth of the disease.

The paper aims to develop three regression models of the COVID-19 epidemic process on given territories and investigate the experimental results of the simulation. The research is targeted at the COVID-19 epidemic process. The research subjects are methods and models of epidemic process simulation, which includes machine learning methods, particularly linear regression, Ridge regression, and Lasso regression.

To achieve the aim of the research following tasks have been formulated:

1. Methods and models of the COVID-19 epidemic process should be analyzed;
2. Data on COVID-19 morbidity should be analyzed;
3. A simulation model of the COVID-19 epidemic process based on linear regression should be developed;
4. A simulation model of the COVID-19 epidemic process based on Ridge regression should be developed;
5. A simulation model of the COVID-19 epidemic process based on Lasso regression should be developed;
6. Experimental evaluation of regression models should be provided;
7. Results obtained during the experimental studies should be analyzed.

The respective contribution of this study is twofold. Firstly, the development of models based on the regression methods will allow estimating the accuracy of simple machine learning methods applied to the simulation of the COVID-19 epidemic process. Secondly, a comparison study of three machine learning models to emergence disease epidemic process simulation will contribute to empirical evaluation of the effectiveness of their application not only to COVID-19 but also to other infectious diseases simulations.

In this paper, section 1, namely current research analysis, provides the current state of COVID-19 epidemic process simulation methods and models. Section 2, namely COVID-19 data analysis, describes the data used within the research and COVID-19 pandemic analysis in Ukraine, Germany, Japan, and South Korea. Section 3, namely Models and methods, provides a brief overview of linear regression, Ridge regression, and Lasso regression methods to develop epidemic process models based on them. Section 4 provides the results of forecasting the COVID-19 new cases in Ukraine, Germany, Japan, and South Korea with developed models. The accuracy and complexity of developed models are estimated. The discussion section discusses the obtained results with Public Health tasks. Conclusions describe the outcomes of the proposed models used.

Given research is part of a complex intelligent information system for epidemiological diagnostics, the concept of which is discussed in [13].

1. Current Research Analysis

Methods for modeling epidemic morbidity originate from the work of Kermack and McKendrick [14], who developed the approaches of Ronald Ross [15] for modeling infectious morbidity. The approach is based on dividing of the population into compartments that correspond to the states of people. A system of differential equations describes the spread of an infectious disease in a given population using infection and recovery rates.

The digitalization of health care has opened up new opportunities for automated diagnostics [16], building medical information systems [17], security of medical data [18], medical data storage [19], virus research [20], and, in particular, for the study and modeling of epidemic processes. The global COVID-19 pandemic has also con-

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tributed to modeling the spread of infectious diseases, attracting research groups from around the world.

Many researchers use the classical compartment approach to COVID-19 simulation. The authors of the paper [21] have applied the classical Susceptible-Infected-Removed (SIR) model to the transmission of COVID-19 disease simulation. Transmission between states is realized by the classical linear incidence rate and considers the nonlinear removal rate, which depends on the hospital-bed population rate. Research [22] has proposed the same structure but with a convex incidence rate. The authors have calculated the disease-free and endemic equilibrium and the basic reproduction number R_0. The results have shown that migration should be strictly prohibited to save humanity from overcoming the pandemic. Also, the isolation of infected ones is the best option to secure a healthy community. Research [23] has proposed to modify the classical SIR model with age structures. The reason for such modification was the hypothesis that the population age distribution has a significant effect on disease spread and mortality rate. Authors have defined disease parameters of the COVID-19 pandemic, such as hospitalization, intensive care, and mortality rate for each age bracket.

Some researchers expand the set of states of the compartment models. Paper [24] presents Susceptible-Exposed-Infected-Recovered (SEIR) model. The proposed models showed that social distancing, wearing masks in public, limiting non-essential travel, frequent hand washing, and other control measures are necessary to avoid the sizeable COVID-19 pandemic. On the other hand, the model has been designed only to look at transmission dynamics, so it does not investigate severity and death. Authors of [25] have modified the SEIR model taking into account the spreading of infection during the latent period. The model is dedicated to evaluating the confinement rate at the first stages of the pandemic outbreak to assess the scenarios that minimize the incidence and the mortality rates. The model does not consider space explicitly as authors have used aggregated data.

Other researchers apply more complex structures of compartment models to simulate the COVID-19 epidemic process. For example, model [26], called SEIHRD, consists of seven states, including Susceptible (S), Exposed (E), Infected (I), Hospitalized (H), Recovered (R), and Death (D), and considers social distancing, as an attitude or behavior which can change the behaviors and decrease contact rates that makes to reduce the transmission of infectious and control the diseases. Paper [27] has proposed deterministic compartmental model SEAMHCRD, which includes various stages of infection, such as Mild, Moderate, Severe, Critical, based on clinical stages of infection. The simulation results have shown that there is no need for complete lockdown, and values on transmission rates can be reduced by proper contact tracing mechanisms and effective social distancing measures. Authors of [28] have added state Asymptomatic and proposed the Susceptible-Asymptomatic-Hospitalized-Isolated-Removal (SEAHIR) model. The dividing of state Infected into three compartments Asymptomatic, Isolated, and Hospitalized, makes it possible to delineate the transmission specifics of each compartment and forecast health requirements. Still, the proposed model does not consider the reinfections and duration of immunity following SARS-CoV-2 infection.

Despite their popularity, classical deterministic compartmental models have several disadvantages:

– high computational complexity;

– the impossibility of making changes to the model. When changing the rules of the dynamics of infectious disease and the virulence of a virus, the system of differential equations has to be rebuilt anew;

– the impossibility of taking into account the heterogeneity of the population. The introduction of features of individuals, such as gender, age, place of work, dramatically complicates the model and makes it unsuitable for practical use;

– the impossibility of extending the model to other diseases and areas of knowledge.

Authors of research [29] say that SIR-like modeling could not be applied to outbreak simulation because it depends on various parameters, most of which quantitative information is not yet available. So, it is applicable only for short-term forecasting. In [30] authors affirm that such models often have conflicting messages that are hard to interpret, and it is almost impossible to distinguish a good model from an unreadable one.

Therefore, to improve the accuracy of forecasting the dynamics of the epidemic process, it is advisable to use approaches based on machine learning. Their advantages are the high accuracy of the constructed forecast, the possibility of retraining the model on updated data, the possibility of using data not only on the incidence but also characterizing the individuals of the population.

Thus, within the framework of this study, the following methodology is proposed. Analyze data on new cases of COVID-19 hosted by the Johns Hopkins Research Center coronavirus aggregator. Analyze the dynamics of the pandemic and control measures in different countries to select countries for verification of machine learning models. Implement three machine learning regression models based on linear regression, Lasso regression, and Ridge regression methods. Build forecasts for various periods, analyze their accuracy and identify tasks for which they can be used in practice. To assess the accuracy and adequacy of the constructed models, use both the relative error and the mean absolute value. To assess the possibility of using the developed models in medical institutions of the healthcare system, evaluate the computational complexity of the models.

2. COVID-19 Data Analysis

The data source used in the given research was the Johns Hopkins Coronavirus Resource Center, which collects available data on cases, death, hospitalization, tests, vaccination and stores it publicly. The data is aggregated and continuously updated.

We used the data on new cases in Ukraine, Germany, Japan, and South Korea for the experimental study. The purpose of selecting these countries is differences in testing, counter-measures, and policy to combat the current pandemic.

As of January 2022, almost 4 million cases of COVID-19 were registered in Ukraine, almost 100 thousand of which ended in death. The first case of the spread of a new coronavirus infection was recorded on March 3, 2020, in the Chernivtsi region after the patient returned from Italy. Despite the constantly implemented anti-epidemic measures, a high incidence rate is observed. In Ukraine, a nationwide quarantine was announced from March 11 to April 3, 2020, which ended with a gradual weakening of anti-epidemic measures on May 11, 2020, May 22, 2020, and June 1, 2020. In April 2020, the “Diy Vdoma” mobile application was introduced to control people, who are required to undergo mandatory self-isolation or observation. Adaptive quarantine in the country is still ongoing, and control measures depend on the region’s distribution into four zones: green, yellow, orange, and red [31]. On February 24, 2021, vaccination against COVID-19 began. However, despite a sufficient number of vaccines, immunization remains the lowest in Europe [32]. Another characteristic of the pandemic in Ukraine is the high level of disinformation and fakes among the population due to the active information campaign of the Russian Federation [33]. As of January 2022, the fourth wave of incidence can be observed.

As of January 2022, almost 9 million cases of COVID-19 were registered in Germany, more than 117 thousand of which are fatal. The first case was registered on January 27, 2020, in Bavaria. From March to May 2020, a hard lockdown was introduced in the country, which began to gradually loosen later [34]. In the fall of 2020, mass protests against quarantine took place, and at the end of October, quarantine was again tightened for a month [35]. On December 27, 2020, the country's official coronavirus vaccination campaign began. As of January 2022, almost 75% of the population has been vaccinated, 80% of whom are under 60 years old [36]. Germany has one of the lowest fatality rates (0.3%), which is associated with almost 100% testing of all suspected virus cases and their isolation [37]. They also note one of the best preparedness for a pandemic globally, associated with a high level of medicine in the country [38]. In January 2022, there is a 4th wave of incidence associated with the spread of a new strain of Omicron.

As of January 2022, 2.3 million cases of COVID-19 were registered in Japan, 18.5 thousand of which are fatal. The first confirmed case in Japan was identified on January 16, 2020, in Kanagawa Prefecture. The state of emergency in the country was announced on April 7, 2020 [39]. It should be noted that Japan was one of the first countries outside of China in which a pandemic began. At the same time, successes in the fight against COVID-19 also show the highest results. This is because even before the pandemic, the Japanese wore masks, even on the streets. At the same time, they monitor their health, nutrition, aggression, and panic are not inherent in Japanese society. The country’s people trust the government and carry out all anti-epidemic measures [40]. At the entrance to the country, careful control is carried out with mandatory testing [41]. When an infected person is detected, a particular protocol is implemented, according to which all contact people are isolated. As of January 2022, 80.5% of the population has been vaccinated [42]. At the same time, the sixth wave of the pandemic is observed.

As of January 2022, more than 760 thousand cases of COVID-19 were registered in South Korea, of which 6.6 thousand are fatal. The first suspected case of a new coronavirus was on January 8, 2020. On February 23, 2020, the highest level of danger was declared. At this time, South Korea became the second country in the world after China in terms of the spread of the virus, as a result of which a hard lockdown was introduced until May 2020 [43]. The country's leadership managed to effectively control the disease in a short time. Mass testing of the population was carried out in the country with the isolation of all infected and contact persons [44]. Such large-scale testing has avoided a further increase in morbidity and mortality. Mass testing also shows the lowest death rate globally after Taiwan (0.4 per 100,000 population). As of January 2022, 86.6% of the population has been vaccinated [45]. At the same time, a new wave of mortality is observed, which is associated with a new strain of Omicron.

3. Models and Methods

Within the framework of this study, three models of the spread of the incidence of COVID-19 were built based on regression analysis. The models are based on linear regression, Ridge regression, and Lasso regression.

Regression analysis is a classic approach to forecasting time series of any nature, easily implemented using modern computing tools. Non-adaptive models make it possible to obtain a forecast of the incidence dynamics for any period. However, they ignore local fluctuations in epidemic indicators and therefore are poorly suited for short-term forecasting. On the other hand, adaptive models are designed to generate forecasts for several weeks ahead and can be used to predict long-term trends.

3.1. Linear Regression

Linear regression is a model of the dependence of the variable x on one or more other variables (factors, regressors, independent variables) with a linear dependence function. Linear regression refers to determining the "line of best fit" through a set of data points and became a simple precursor to the non-linear methods used to train neural networks [46]. The advantage of models based on linear regression is the ease of implementation.

The linear regression method consists in selecting such coefficients of a linear equation with one or more independent variables so that this equation best predicts the value of the dependent variable. The result of linear regression can be represented as a straight line in a plane, minimizing the discrepancy between predicted and actual values.

Let's consider two continuous variables

$$x = (x_1, x_2, \dots, x_n), \quad (1)$$

$$y = (y_1, y_2, \dots, y_n). \quad (2)$$

The country's leadership managed to effectively control the disease in a short time. If we assume that y depends on x, and changes in x cause changes in y, we can define a regression line (regression of y on x) that best describes the straight-line relationship between these two variables.

A mathematical equation that describes a simple linear regression model is

$$y = f(x,b) + \varepsilon, \quad (3)$$

where b are parameters of the model;

ε is a random model error.

The regression function has the following form:

$$f(x,b) = b_0 + b_1x_1 + b_2x_2 + \dots + b_kx_k, \quad (4)$$

where b_j are regression parameters;

x_j are model factors;

k is a number of model factors.

3.2. Ridge Regression

Ridge regression is the enhancement of linear regression with improved error tolerance [47]. The model imposes restrictions on the regression coefficients to obtain a result closer to actual data. The advantage of using Ridge regression is that this result is much easier to interpret. A method is applied to deal with data overabundance when independent variables correlate with each other.

The following formula can describe Ridge regression. Let X be a suitably centered and normalized matrix, which corresponds to the case when the regression problem under study is expressed in a correlation form. Then, for the model, we can obtain estimates of the parameters b by the formula:

$$b(\lambda) = (X^TX + \lambda I)^{-1}X^Ty. \quad (5)$$

As the λ parameter increases, the estimates decrease in absolute value and tend to 0, while λ tends to infinity. The choice of alpha value is guided by the following factors [48]:

– at a certain value of λ, the system stabilizes and acquires the usual properties of an orthogonal system;

– coefficients with obviously wrong signs at $\lambda = 0$ can be changed to make the sign fit;

– coefficients cannot have exorbitantly high absolute values compared to the factors concerning representing rates of change;

– the residual sum of squares should not increase to unreasonably high values. It should not be too large in relation to the minimum residual sum of squares or in relation to the value that corresponds to acceptable process variations.

3.3. Lasso Regression

Lasso regression (Least absolute shrinkage and selection operator) is similar to Ridge regression, except that the regression coefficients can be zero (some features are excluded from the model) [49].

The method introduces a constraint on the norm of the vector of model coefficients. This leads to the conversion to 0 of some coefficients of the model. The method leads to an increase in the stability of the model in the case of a large number of conditionality of the feature matrix X, allowing you to get interpretable models by selecting features that have the most significant impact on the response vector.

Lasso regression can be described by the following equation:

$$L(w) = \frac{1}{2}\sum_{i=1}^{N}(f(x_i, w)^2 + \lambda \sum_{j=0}^{p}|w_j|. \quad (6)$$

The Lasso tends to make the w part of the value become 0, so it can be used as an object selection since the regular term is not output everywhere here, so the gradient-based method cannot be used directly.

The considered machine learning models are not ideal. When used with complex data, errors are inevitable.

Therefore, when implementing them and applying them to actual data, the source should be considered. Uncertain factors may cause data errors during data collection and storage.

In our case, the data is collected and cleaned. Therefore, to improve the accuracy of the simulation, we can optimize the model parameters to balance bias and variance.

One reason for the deviation is using a linear method to solve a non-linear problem. The high variance is that the model is too complex or overfitting.

If the deviation decreases, the variance increases accordingly, and if the variance decreases, the deviation increases accordingly. Therefore, it is necessary to find the optimal set of parameters in machine learning models. Such a set of parameters can weigh the variance and variance of the model so that the model's performance becomes optimal.

Therefore, these factors should be considered when assessing the model's adequacy.

4. Results

The models described in Section 3 were implemented in the Python programming language. An experimental study was carried out to predict the dynamics of the spread of the epidemic process of COVID-19 for 3, 7, 10, 14, 21 and 30 days.

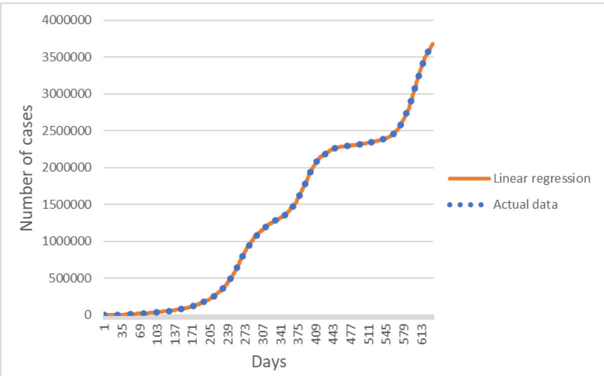
4.1. COVID-19 New Cases Forecasting

We used data from the Johns Hopkins Coronavirus Resource Center on new cases of COVID-19 reported daily for experimental study. Morbidity dynamics models have been applied to predict new cases of COVID-19 in Ukraine, Germany, Japan, and South Korea.

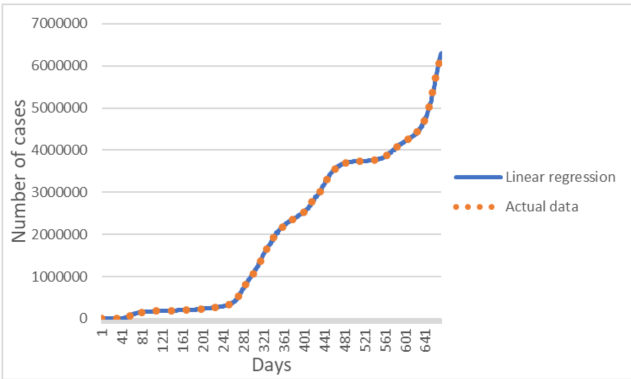
Figure 1 shows the results of predicting new cases of COVID-19 obtained using a linear regression model.

Figure 2 shows the results of predicting new cases of COVID-19 obtained using the Ridge regression model.

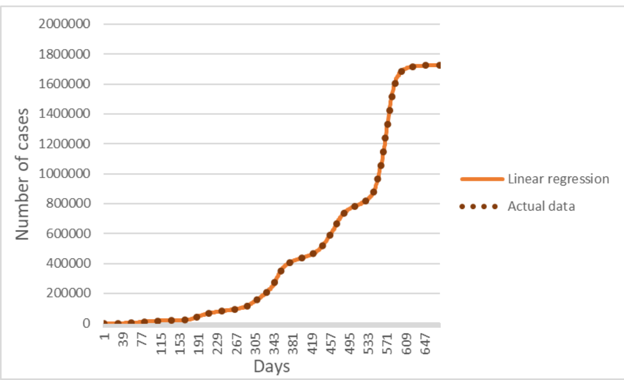
Figure 3 shows the results of predicting new cases of COVID-19 obtained using the Lasso regression model.



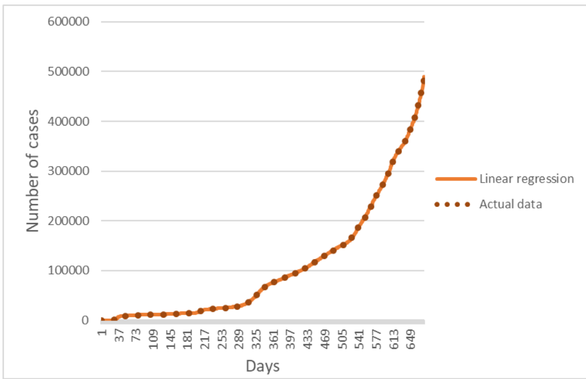
Ukraine



Germany



Japan



South Korea

Fig. 1. Forecasting of COVID-19 new cases by the linear regression model

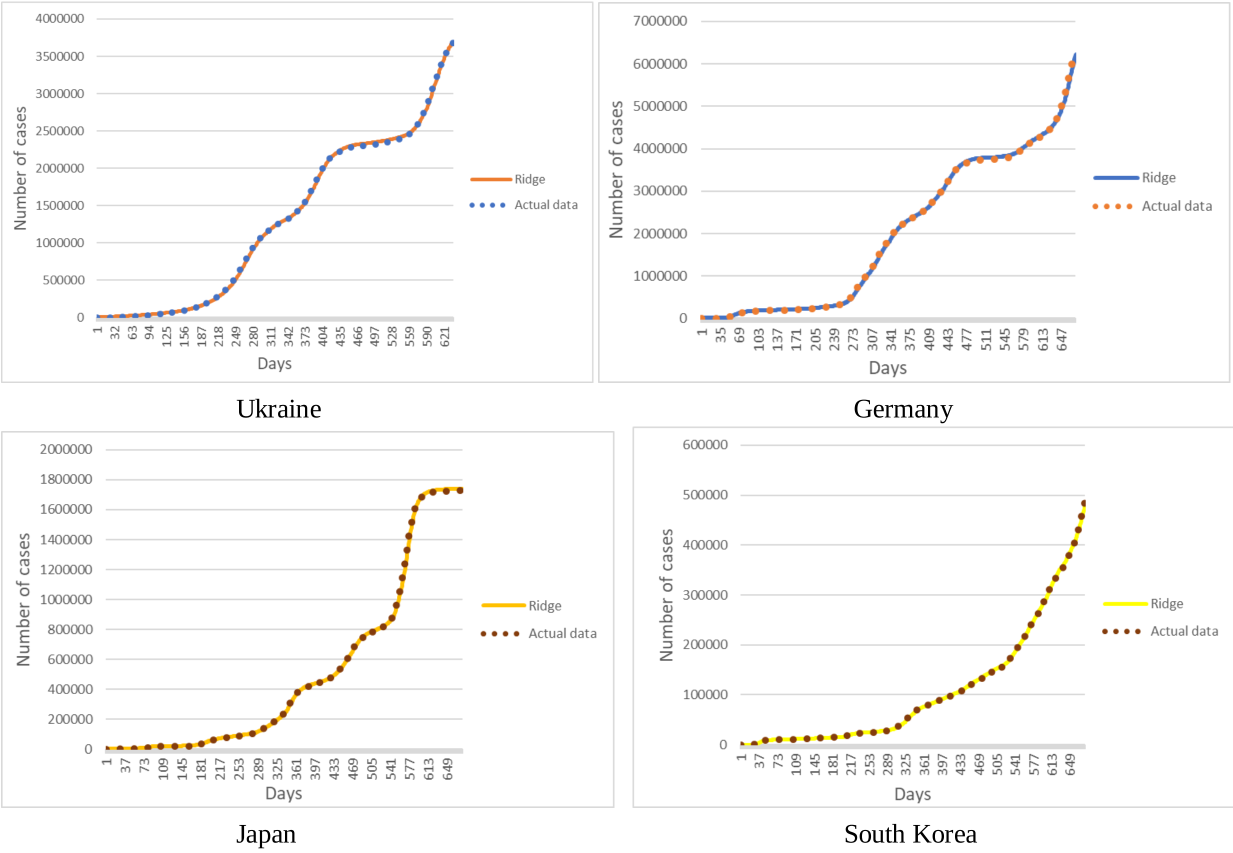


Fig. 2. Forecasting of COVID-19 new cases by the Ridge regression model

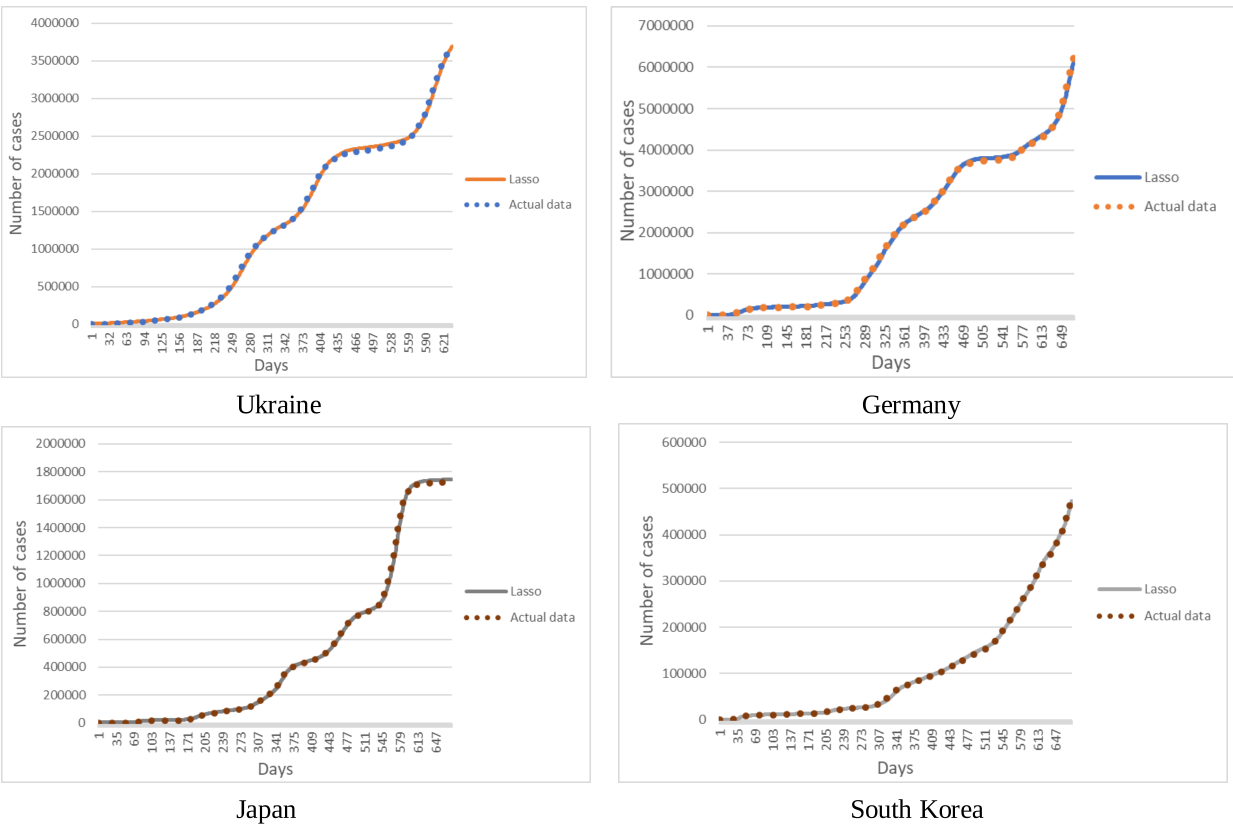


Fig. 3. Forecasting of COVID-19 new cases by the Lasso regression model

4.2. Forecast Accuracy Estimation

To assess the accuracy of the constructed forecasts, relative errors were calculated for a retrospective morbidity forecast for 3, 7, 10, 14, 21, and 30 days. Using the relative error of the training data, one can assess the adequacy of the constructed model. The relative error of forecast data shows the accuracy of the constructed forecast of new cases of COVID-19.

Table 1 shows the accuracy of built regression models to estimate new cases of COVID-19 in Ukraine.

Table 1

Relative error of forecast for Ukraine (%)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Training 3	0.51947	7.218654	9.167315
Predict 3	0.01954	0.077852	0.049995
Training 7	0.522203	7.26747	9.229571
Predict 7	0.070956	0.064677	0.039235
Training 10	0.524341	7.302967	9.274878
Predict 10	0.07866	0.152506	0.150389
Training 14	0.526901	7.351176	9.335145
Predict 14	0.097589	0.198273	0.260624
Training 21	0.531659	7.43091	9.434995
Predict 21	0.107914	0.40696	0.560994
Training 30	0.538668	7.527658	9.556304
Predict 30	0.100237	0.695296	0.942586

Table 2 shows the accuracy of built regression models to estimate new cases of COVID-19 in Germany.

Table 2

Relative error of forecast for Germany (%)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Training 3	1.342267	3.078552	3.587338
Predict 3	0.380621	1.243194	1.735014
Training 7	1.350275	3.082998	3.592783
Predict 7	0.199158	1.894353	2.306608
Training 10	1.355431	3.089665	3.599147
Predict 10	0.21654	1.835582	2.295945
Training 14	1.362386	3.0921	3.602342
Predict 14	0.227986	2.086237	2.527049
Training 21	1.37433	3.10433	3.61621
Predict 21	0.25063	2.06512	2.481326
Training 30	1.390609	3.132654	3.648929
Predict 30	0.253488	1.807561	2.164123

Table 3 shows the accuracy of built regression models to estimate new cases of COVID-19 in Japan.

Table 3

Relative error of forecast for Japan (%)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Training 3	2.249401	15.43302	16.94114
Predict 3	0.024418	0.796758	1.006096
Training 7	2.263346	15.52653	17.04295
Predict 7	0.022876	0.797736	1.006635
Training 10	2.273905	15.59745	17.12016
Predict 10	0.023429	0.798279	1.00748
Training 14	2.288174	15.6931	17.22431
Predict 14	0.02231	0.797551	1.006077
Training 21	2.313564	15.86356	17.40992
Predict 21	0.021923	0.795017	1.002993
Training 30	2.347055	16.08861	17.65497
Predict 30	0.02175	0.792057	0.999613

Table 4 shows the accuracy of built regression models to estimate new cases of COVID-19 in South Korea.

Table 4

Relative error of forecast for South Korea (%)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Training 3	0.591071	1.488872	2.245665
Predict 3	0.440518	1.134591	1.642878
Training 7	0.594315	1.492614	2.25156
Predict 7	0.230382	1.002351	1.460166
Training 10	0.595863	1.49597	2.257425
Predict 10	0.241142	0.940384	1.33219
Training 14	0.599411	1.503444	2.269125
Predict 14	0.182298	0.768649	1.079225
Training 21	0.604283	1.517709	2.291235
Predict 21	0.176351	0.597856	0.831502
Training 30	0.611314	1.534434	2.317176
Predict 30	0.160347	0.537641	0.748017

Table 5

Mean absolute error of cumulative new cases forecast for Ukraine (number of cases)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Predict 3	713.6667	2846.667	1831.667
Predict 7	2566	2350.286	1427.857
Predict 10	2833.5	5480.3	5395.8
Predict 14	3419.855	32607.11	33763.41
Predict 21	3790.905	14160.19	19474.24
Predict 30	3460.167	23371.93	31661.63

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Table 6
Mean absolute error of cumulative new cases forecast for Germany (number of cases)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Predict 3	23663.67	77680.67	108349
Predict 7	12345.29	116295.4	141743
Predict 10	13156	111274.2	139142.9
Predict 14	13546.71	123638.3	149939.1
Predict 21	14301.62	118556.9	142688.4
Predict 30	13901.9	101110.5	121276.8

Table 7
Mean absolute error of cumulative new cases forecast for Japan (number of cases)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Predict 3	421.6667	13759	17374
Predict 7	395	13774.29	17381.29
Predict 10	404.5	13782.5	17394.4
Predict 14	385.1429	13768.43	17368.29
Predict 21	378.381	13721.57	17311.14
Predict 30	375.2667	13665.5	17246.5

Table 8
Mean absolute error of cumulative new cases forecast for South Korea (number of cases)

Duration of forecast (days)	Linear Regression	Ridge Regression	Lasso Regression
Predict 3	2024.333	5250	7593.667
Predict 7	1053.714	4552.429	6630.429
Predict 10	1082.7	4221.4	5984.9
Predict 14	815.6429	3422.857	4812.714
Predict 21	766.1905	2624.667	3656.19
Predict 30	677.6	2295.4	3197

Relative error rates of epidemic process models are not informative for health and public health workers, so Tables 5-8 show mean absolute errors of regression models for cumulative rates of daily COVID-19 incidence.

4.3. Models Complexity Estimation

Let us estimate the computational complexity of the linear regression model. Suppose X is a matrix (n x m) and y is a vector of results. In that case, transposing the matrix (n x m) will take O (n * m) time, (X'X) will take O (n * m^2) time, inverting the matrix (m x m) will take O (m^3) time, (X'^y) will take O (n * m) time, and matrix (m x m) and (m x 1) multiplication will take O (m^2) time. Thus, the execution time of the model is O (n * m + n * m^2 + m^3 + n * m+m^2). Therefore, the actual running time is O (m^2 (n + m). At the same time, the probability of an increase in the number of observations is higher than the number of attributes. Therefore, if the model is used only to predict daily new cases of COVID-19 cases, i.e. the number of attributes will remain constant when calculating the elapsed time, you can ignore the number of terms m. Then the time complexity of linear regression will be O (n).

The computational complexity of Ridge and Lasso regressions is approximately the same, both of them are cubic. Highly correlated data produce coefficient estimates with large variance, which can make the estimates unreliable. Lasso Regression removes the correlated coefficients and simply selects one of the sets of correlation coefficients. The Lasso regression model is that it chooses which coefficients to exclude. Ridge regression makes the coefficients less correlated. Both operations with coefficients introduce a systematic error into the forecast. Thus, the Lasso regression model should be used when it is necessary to reduce the number of instrumental variables since we do not evaluate their influence. The Ridge regression model should be used if it is important that the model parameters do not fall out of it.

5. Discussion

The constructed models were applied to calculate the forecast of new cases of COVID-19 for 6 periods:

– the forecast for 3 days is the nearest forecast for implementing of the operational analysis of the epidemic situation. At the same time, the main drawback of the forecast is the possibility of unreliable statistics in a three-day period, which is caused by weekends or holidays. Such a decrease in registered incidence on weekends and holidays, and, on the other hand, an increase in statistics on subsequent days, is observed in all analyzed countries;

– the forecast for 7 days can also be used for operational analysis of the situation. At the same time, 7 days make up a week, so the outliers associated with the registration of morbidity on weekends are smoothed out in such a forecast, i.e. the dynamics of the forecast is similar to the actual incidence of COVID-19. Also, 7 days is the minimum incubation period for COVID-19, so new cases will also fall into this forecast [50];

– the 10-day forecast can be used to assess the development of the current epidemic situation. Such a prognosis also includes those already ill without external manifestations, etc. The average incubation period for COVID-19 is 10 days [50];

– the 14-day forecast assesses the effectiveness of the anti-epidemic measures taken today. Because 14 days is the maximum incubation period for COVID-19 [50], such a forecast includes both new cases of the disease and those who have already become infected, but so far without external manifestations;

– forecasts for 21 and 30 days can be used to study the dynamics of the virus. Based on such forecasts, it is possible to assess the need for anti-epidemic measures, and what they should be. Analyzing such forecasts, one can estimate the speed of filling beds and the need to provide hospitals with new beds, the required number of beds with connected oxygen, the purchase of medicines, and the required number of medical workers.

When choosing a model, one should also pay attention to the possibility of overfitting, i.e. situations when the error probability of the trained algorithm on the objects of the test sample is significantly higher than the average error on the training sample. An analysis of the regression models built within the framework of this study showed that they are not overfitted.

The minimum required number of observations for all constructed models was estimated to obtain a significant result. For a linear regression model, this is 25 days; for Ridge and Lasso regression models, this is 40 days for any samples.

Also of interest is the observation of an increase in errors with an increase in the forecast period for Ukraine, slight fluctuations in error depending on the forecast period for Germany, and a decrease in the error with an increase in the duration of the forecast for Japan and South Korea. Because since this situation is observed for all three models, we can conclude that the accuracy of the models depends on the correctness of the statistics. Thus, in Japan and South Korea, there is a constant testing of the entire population, i.e. asymptomatic patients are identified, and the actual incidence of COVID-19 is close to that reported. Germany also has a high level of testing. However, vaccination rates are lower than in Japan and South Korea, and asymptomatic cases may not be included in the statistics. It can be concluded that the registered statistics in Ukraine differ from the actual ones. This is due to mandatory testing only when traveling abroad if this is required by the entry rules of a certain country. Those, testing covers severe cases of COVID-19 that require hospitalization, and most asymptomatic patients remain behind the official statistics.

Conclusions

The paper describes experimental research on implementing of three regression models of the COVID-19 epidemic process. These are models of linear regression, Ridge regression, and Lasso regression. Models were verified by COVID-19 daily new cases statistics for Ukraine, Germany, Japan, and South Korea, provided by the Johns Hopkins Coronavirus Resource Center.

The scientific novelty of the study lies in the development and study of models of the epidemic process of emerging diseases using the example of COVID-19, which are based on state-of-the-art methods of regression analysis. Unlike others, the study analyzed forecasting for different periods, which allows us to evaluate the possibility of using the calculated dynamics of the epidemic process for different tasks.

The practical novelty of the study lies in determining the dynamics of the COVID-19 epidemic process for different territories. At the same time, it is shown that the accuracy of the models depends on the completeness of registered cases of COVID-19. The tasks that can be solved by public health workers depending on the period of the available forecast are analyzed.

All built models have sufficient accuracy to make decisions on the implementation of anti-epidemic measures to combat the COVID-19 pandemic in the selected area. Depending on the forecast period, regression models can be used to solve the problems of operational analysis of the epidemic situation, analysis of the effectiveness of already implemented anti-epidemic measures, medium-term planning of resources needed to combat the pandemic, etc.

The nature of the dynamics of model errors depending on the forecasting period indicates a high agreement between actual and registered data on the incidence of COVID-19 in Japan and South Korea, sufficient completeness of data on new cases of COVID-19 in Germany, and insufficient registration of asymptomatic and contact patients with COVID-19 in Ukraine.

Future research development. Despite the high accuracy of the constructed forecasts of new cases of COVID-19, machine learning models do not allow to identification of the factors that affect the dynamics of the epidemic process, which is an important task for public health professionals. Therefore, the further development of this study is the development of multi-agent models of the COVID-19 epidemic process in selected areas and combining them with machine learning models to improve the accuracy of forecasts. The development of such combined models will allow taking into account the intellectual behavior of individuals in the population under study, social factors affecting the development of the epidemic process, as well as assessing the effectiveness of specific anti-epidemic measures, such as full or partial lockdowns, wearing masks, social distancing, vaccination, etc.

Contributions of authors: conceptualization – **D. Chumachenko**; methodology – **D. Chumachenko**, **I. Meniailov**; formulation of tasks – **D. Chumachenko**, **I. Meniailov**; analysis – **D. Chumachenko**, **I. Meniailov**, **K. Bazilevych**, **O. Chub**; development of models – **D. Chumachenko**, **I. Meniailov**, **K. Bazilevych**, **O. Chub**; software – **D. Chumachenko**, **I. Meniailov**,

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ПРО МОДЕЛЮВАННЯ ЕПІДЕМІЧНОГО ПРОЦЕСУ COVID-19: ДОСЛІДЖЕННЯ ТРЬОХ РЕГРЕСІЙНИХ ПІДХОДІВ

Д. І. Чумаченко, Є. С. Меняйлов, К. О. Базілевич, О. І. Чуб

Спалах нової коронавірусної інфекції був вперше зареєстрований в Ухані, Китай, у грудні 2019 року. 30 січня 2020 року Всесвітня організація охорони здоров'я оголосила спалах надзвичайною ситуацією в галузі

громадської охорони здоров'я, що має міжнародне значення, а 11 березня – пандемією. Станом на січень 2022 року у всьому світі зареєстровано понад 340 мільйонів випадків; Підтверджено понад 5,5 мільйонів смертей, що робить пандемію COVID-19 однією з найбільш смертоносних в історії. Цифровізація всіх сфер суспільства дає можливість використовувати математичне та імітаційне моделювання вивчення розвитку вірусу. Побудова адекватних моделей епідемічного процесу дозволить не тільки прогнозувати його динаміку, але й проводити експериментальні дослідження з виявлення факторів, що впливають на розвиток пандемії, визначати поведінку вірусу на окремих територіях, оцінювати ефективність заходів, спрямованих на припинення поширення інфекції, а також оцінити ресурси, необхідні для протидії епідемічного зростання захворювання **Метою** статті є розробка трьох регресійних моделей епідемічного процесу COVID-19 на заданих територіях та дослідження експериментальних результатів моделювання. **Об'єкт дослідження** – епідемічний процес COVID-19. **Предмет дослідження** – моделі та методи моделювання епідемічного процесу, що включають методи машинного навчання: лінійну регресію, Рідж регресію та регресію Лассо. Для досягнення мети дослідження ми використовували **методи** прогнозування та побудували регресійні моделі епідемічного процесу COVID-19. В **результаті** експериментів з розробленими моделями було отримано прогнозну динаміку епідемічного процесу COVID-19 в Україні, Німеччині, Японії та Південній Кореї на 3, 7, 10, 14, 21 та 30 днів. Такий прогноз може бути використаний особами, що приймають рішення про впровадження протиепідемічних заходів, для вирішення завдань оперативного аналізу епідемічної ситуації, аналізу ефективності вже реалізованих протиепідемічних заходів, середньострокового планування ресурсів, необхідних для боротьби з пандемією, тощо. **Висновки**. У статті описано експериментальні дослідження реалізації трьох регресійних моделей епідемічного процесу COVID-19. Це моделі лінійної регресії, регресії Ріджа та регресії Лассо. Моделі були перевірені щоденною статистикою нових випадків COVID-19 в Україні, Німеччині, Японії та Південній Кореї, наданої Ресурсним центром з коронавірусу Університету Джона Хопкінса. Всі побудовані моделі мають достатню точність для прийняття рішень щодо проведення протиепідемічних заходів щодо боротьби з пандемією COVID-19 на вибраній території. Залежно від періоду прогнозу регресійні моделі можуть використовуватися для вирішення різних завдань громадської охорони здоров'я.

Ключові слова: епідемічна модель; епідемічний процес; моделювання епідемії; моделювання; COVID-19; Рідж регресія; регресія Лассо; лінійна регресія.

О МОДЕЛИРОВАНИИ ЭПИДЕМИЧЕСКОГО ПРОЦЕССА COVID-19: ИССЛЕДОВАНИЕ ТРЕХ РЕГРЕССИОННЫХ ПОДХОДОВ

Д. И. Чумаченко, Е. С. Меняйлов, К. А. Базилевич, О. И. Чуб

Вспышка новой коронавирусной инфекции была впервые зарегистрирована в Ухане, Китай, в декабре 2019 года. 30 января 2020 года Всемирная организация здравоохранения объявила вспышку чрезвычайной ситуацией в области общественного здравоохранения, имеющей международное значение, а 11 марта — пандемией. По состоянию на январь 2022 года во всем мире зарегистрировано более 340 миллионов случаев; Подтверждено более 5,5 миллионов смертей, что делает пандемию COVID-19 одной из самых смертоносных в истории. Цифровизация всех сфер общества дает возможность использовать математическое и имитационное моделирование для изучения развития вируса. Построение адекватных моделей эпидемического процесса позволит не только прогнозировать его динамику, но и проводить экспериментальные исследования по выявлению факторов, влияющих на развитие пандемии, определять поведение вируса на отдельных территориях, оценивать эффективность мер, направленных на прекращение распространения инфекции, а также оценить ресурсы, необходимые для противодействия эпидемическому росту заболевания. **Целью** статьи является разработка трех регрессионных моделей эпидемического процесса COVID-19 на заданных территориях и исследование экспериментальных результатов моделирования. **Объект исследования** – эпидемический процесс COVID-19. **Предмет исследования** – модели и методы моделирования эпидемического процесса, включающие в себя методы машинного обучения: линейную регрессию, Ридж регрессию и регрессию Лассо. Для достижения цели исследования мы использовали **методы** прогнозирования и построили регрессионные модели эпидемического процесса COVID-19. В **результате** экспериментов с разработанной моделью была получена прогнозная динамика эпидемического процесса COVID-19 в Украине, Германии, Японии и Южной Корее на 3, 7, 10, 14, 21 и 30 дней. Такой прогноз может быть использован лицами, принимающими решения о проведении противоэпидемических мероприятий, для решения задач оперативного анализа эпидемической ситуации, анализа эффективности уже реализованных противоэпидемических мероприятий, среднесрочного пла-

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нирования ресурсов, необходимых для борьбы с пандемией и т.д. **Выводы.** В статье описаны экспериментальные исследования реализации трех регрессионных моделей эпидемического процесса COVID-19. Это модели линейной регрессии, регрессии Риджа и регрессии Лассо. Модели были проверены ежедневной статистикой новых случаев COVID-19 в Украине, Германии, Японии и Южной Корее, предоставленной Ресурсным центром по коронавирусу Университета Джона Хопкинса. Все построенные модели обладают достаточной точностью для принятия решений о проведении противоэпидемических мероприятий по борьбе с пандемией COVID-19 на выбранной территории. В зависимости от периода прогноза регрессионные модели могут использоваться для решения различных задач общественного здравоохранения.

Ключевые слова: эпидемическая модель; эпидемический процесс; моделирование эпидемии; моделирование; COVID-19; Ридж регрессия; регрессия Лассо; линейная регрессия.

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