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IMPACT OF WAR ON COVID-19 PANDEMIC IN UKRAINE: THE SIMULATION STUDY

*The COVID-19 pandemic has posed a challenge to public health systems worldwide. As of March 2022, almost 500 million cases have been reported worldwide. More than 6.2 million people died. The war that Russia launched for no reason on the territory of Ukraine is not only the cause of the death of thousands of people and the destruction of dozens of cities but also a large-scale humanitarian crisis. The military invasion also affected the public health sector. The impossibility of providing medical care, non-compliance with sanitary conditions in areas where active hostilities are occurring, high population density during the evacuation, and other factors contribute to a new stage in the spread of COVID-19 in Ukraine. Building an adequate model of the epidemic process will make it possible to assess the actual statistics of the incidence of COVID-19 and assess the risks and effectiveness of measures to curb the curse of the disease epidemic process. The article aims to develop a simulation model of the COVID-19 epidemic process in Ukraine and to study the results of an experimental study in war conditions. The research is **targeted** at the epidemic process of COVID-19 under military conditions. The **subjects** of the study are models and methods for modeling the epidemic process based on statistical machine learning methods. To achieve the study's aim, we used forecasting **methods** and built a model of the COVID-19 epidemic process based on the polynomial regression method. Because of the experiments, the accuracy of predicting new cases of COVID-19 in Ukraine for 30 days was 97,98%, and deaths of COVID-19 in Ukraine – was 99,87%. The model was applied to data on the incidence of COVID-19 in Ukraine for the first month of the war (02/24/22 - 03/25/22). The calculated predictive values showed a significant deviation from the registered statistics. **Conclusions.** This article describes experimental studies of implementing the COVID-19 epidemic process model in Ukraine based on the polynomial regression method. The constructed model was sufficiently accurate in deciding on anti-epidemic measures to combat the COVID-19 pandemic in the selected area. The study of the model in data on the incidence of COVID-19 in Ukraine during the war made it possible to assess the completeness of the recorded statistics, identify the risks of the spread of COVID-19 in wartime, and determine the necessary measures to curb the epidemic curse of the incidence of COVID-19 in Ukraine. The investigation of the experimental study results shows a significant decrease in the registration of the COVID-19 incidence in Ukraine. An analysis of the situation showed difficulty in accessing medical care, a reduction in diagnosis and registration of new cases, and the war led to the intensification of the COVID-19 epidemic process.*

Keywords: *epidemic model; epidemic process; epidemic simulation; simulation; COVID-19; polynomial regression; war.*

Introduction

In December 2019, the world faced an unprecedented global pandemic of new coronavirus infections in recent history. Since the first registration in Wuhan (China) [1], the SARS-CoV-2 virus has spread to all corners within a few months. Furthermore, on March 11, 2020, the World Health Organization declared a global pandemic of COVID-19 [2]. As of March 2022, almost 500 million cases have been reported worldwide. Over 6.2 million people died.

People bear the COVID-19 in different ways. Most patients experience mild to moderate symptoms of the disease. However, some suffer from complications and require hospitalization. The most common symptoms include fever, cough, fatigue, and loss of taste or smell [3]. Less common symptoms include pain and sore throat, headache, diarrhea, muscle and joint pain, skin rash, redness, and irritation of the eyes [4]. Patients requiring hospitalization experience shortness of breath, chest pain, speech impairment, impaired motor function, and confusion [5].

An essential tool for containing the global COVID-19 pandemic has been the rapid development of vaccines against the virus. Vaccination is critical to contain the pandemic, and adequate testing and preventive measures are already in place. In Ukraine, the vaccination campaign has started in February, 2021 according to the National immunization plan. Plan provided the priority vaccination of risk groups for severe illness and people in critical professions. However, in June 2021 vaccination became available to everyone. And in November 2021 the Ministry of Health regulated mandatory vaccination of specific population groups. Thus, employees of local governments, state and municipal health care institutions, as well as employees of other municipal institutions and organizations need at least one dose of the vaccine to be allowed to work.

The global pandemic has stimulated the development of digital transformation in many areas, such as business [6], education [7], and public administration [8]. Digital transformations have not bypassed the healthcare sector [9], including fighting the pandemic. Many research groups have joined forces to develop models and methods for studying vaccines [10], diagnostics [11], drugs [12], the virus spread [13], and evaluating the effectiveness of control measures [14].

On February 24, 2022, Russia invaded Ukraine for no reason and unleashed a ruthless and bloody war. In addition to thousands of dead, destroyed cities, and millions of refugees, the war has caused a humanitarian crisis in Ukraine. The military invasion also affected the public health sector.

Thus, the paper aims to develop a simulation model of the COVID-19 epidemic process in Ukraine and investigate the experimental results in war conditions. The research is targeted at the COVID-19 epidemic process during the war. The research subjects are methods and models of epidemic process simulation based on statistical machine learning.

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 in Ukraine should be analyzed;
3. Impact of the war on public health facilities in Ukraine should be analyzed;
4. A simulation model of the COVID-19 epidemic process based on polynomial regression should be developed;
5. Verification of polynomial regression model should be provided;
6. Estimation of COVID-19 epidemic process dynamics during the first month of the war in Ukraine 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 polynomial regression method will allow estimating the accuracy of simple machine learning methods applied to the simulation of the COVID-19 epidemic process in Ukraine. Secondly, simulation results will allow us to assess the actual state of the COVID-19 pandemic in Ukraine during the war, which will allow us to identify the necessary measures to reduce the incidence.

In this paper, section 1, namely the current research analysis, provides the current state of COVID-19 epidemic process simulation methods and models. Section 2, namely Data Analysis, describes the background of the COVID-19 epidemic process in Ukraine, the impact of the Russian military invasion on Public Health, and analyses the data sources of COVID-19 morbidity applicable for given research. Section 3, namely Materials and Methods, provides a methodology of research, a brief overview of the polynomial regression method, and verification methods of the prognostic models. Section 4 provides the results of forecasting the COVID-19 new and death cases in Ukraine with the developed model and estimation of the actual dynamics of the COVID-19 epidemic process during the war. The discussion section discusses the obtained results from the epidemiology view. Conclusions describe the outcomes of the investigation.

Given research is part of a complex intelligent information system for epidemiological diagnostics, the concept of which is discussed in [15].

1. Current Research Analysis

Research on epidemic processes using mathematical methods dates back to the 19th century. The best-known approach that is being developed and is still in use is the compartmental approach proposed by Kermack and McKendrick [16]. It consists in dividing the population into compartments. The basic model includes three compartments: S —susceptible, I—infected, R—recovered (removed). The epidemic process is described in the simulated population using a system of differential equations.

The pathogen of COVID-19 is similar to pathogens of two other recent outbreaks SARS and MERS, which were also caused by coronavirus [17].

In [18], a discrete mathematical model was proposed to study the transmission of SARS, and, with its help, the basic reproduction number was determined. The results showed the effectiveness of early quarantine and the need for its high coverage to control the SARS epidemic. It was shown in [19] that classical models of the SIR type could not explain the patterns of SARS propagation in different regions. At the same time, the authors concluded that the first wave of the SARS epidemic immunized a particular part of the population and protected it from the second wave. A review of SARS models conducted in [20] showed that the estimate of the basic reproductive number for SARS diverges in different models. An essential finding of the review is that SARS responses were developed purely through simulation and include quarantine restrictions and an understanding of the impact of population heterogeneity on virus transmission patterns.

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The study [21] is devoted to developing a compartmental model of the Susceptible-Infected type for modeling MERS. The simulation results estimate the base reproduction number and its impact on controlling the outbreak. In [22], a four-dimensional dynamic model of MERS propagation was developed. The authors find the global stability of the equilibrium of the model and conclude that it is possible to control the spread of MERS by reducing the level of DPP4 expression. In [23], a compartmental approach is used to study the epidemic process of MERS. Simulation results have shown that the base reproductive number of the MERS outbreak in South Korea is several times that of the Ebola outbreak in West Africa. The study also says that interventions in the earliest stages of the epidemic were needed to prevent an outbreak.

The compartmental approach is also used to model the dynamics of the spread of COVID-19. In [24], based on the simplest SIR model, the authors study the temporal evolution of populations in different territories. Various significant parameters of the spread of the virus in different communities are monitored. As a result of modeling, the authors conclude that it is possible to contain the COVID-19 pandemic. From the model's point of view, the results are reliable, but in an actual situation, it is impossible to introduce specific control measures to reduce the epidemic growth, i.e., affect parameters of the model.

Article [25] also applies the simplest SIR model to modeling the dynamics of COVID-19. In addition to the main parameters, the model also includes the influence of the media on public opinion. Modeling shows that when the base reproduction number is less than one, the model exhibits non-linear phenomena, including saddle-node, reverse, and Hopf bifurcations. However, from the point of view of epidemiology, when the basic reproductive number is reduced to a value less than one, the epidemic process fades naturally. The article [26] is also devoted to assessing the basic reproductive number. The authors supplement the classical SIR model with the state E – exposed. The study estimates the basic reproduction number for the natural spread of COVID-19, which is not possible in reality. The inability to include external factors that affect the dynamics of morbidity in the model does not allow us to obtain practically significant results.

Also, extensions of the classical SIR model are widely used for modeling COVID-19. For example, in [27], the SIR model is extended to seven states: susceptible (S), exposed (E), infectious (I), quarantined (Q), recovered (R), deaths (D), and vaccinated (V). At the same time, the simulation results show high accuracy in predicting the dynamics of COVID-19 for up to two weeks. The study [28] extends the classical SIR model to SEAHIR (Susceptible-Exposed-Asymptomatic-Hospitalized-Isolated-Removed). At the same time, the model allows short-term forecasting. Furthermore, with various possible states of the population, re-infections and vaccinations are ignored.

However, compartmental models have several disadvantages. Thus, in [29], models based on the SIR approach could not predict the actual spread and nature of the COVID-19 epidemic in the long term. At the same time, the weak point of this approach is the incorrect formulation of assumptions about the behavior of the epidemic process. In addition, among the disadvantages of the compartmental approach, one can single out the high complexity of the models. In order to accurately display the population in which the epidemic process takes place, it is necessary to construct complex multi-dimensional differential equations. At the same time, with the advent of each new strain, the system of differential equations must be built anew, and the values of the coefficients must be selected following the current data in the required territory. This greatly complicates the use of such models in practice.

The agent-based approach allows for avoiding these shortcomings. Using agent-based models can quickly make changes to the rules for the spread of the virus, the structure of the population, and other parameters. As an agent, individuals of a population are usually presented. They can be in different states, similar to the compartmental approach. Moreover, the transition between states is carried out during the interaction of agents with each other and the environment. Thus, an epidemic process is modeled in a population. Furthermore, experimental studies with agent-based models make it possible to identify factors that affect the dynamics of morbidity and evaluate the effectiveness of measures to reduce epidemic development.

In [30], an agent-based model of the spread of COVID-19 Covasim was proposed, which considers demographic information about the population, transmission of the virus in various social groups, transmissibility based on viral load, and many other factors. The model's primary purpose is to evaluate the impact of various interventions on the COVID-19 epidemic. The model assumes customization for different territories. For example, in [31], an extension of Covasim for the territory of Poland was proposed. Adding to the original model allows considering the specifics of Poland's life, work, and social conditions to evaluate and compare strategies to reduce the spread of COVID-19. In [32], the Covasim model was extended and applied to the territory of Vietnam in order to predict future outbreaks of COVID-19. The results showed the importance of adhering to mask-wearing and testing policies.

Agent-based models are also used to solve narrower problems. For example, in [33], the authors assess the risks of transmission of COVID-19 in institutions using an agent-based model. Hypothetical scenarios demonstrating the effectiveness of the proposed model are considered. The model described in [34] simulates the spread of COVID-19 in New York, allowing for tracking the temporal evolution of the virtual city and agent community in terms of infection, asymptomatic, recovery, or hospitalization. The results show that relaxing social distancing measures can increase hospital admissions by more than 30%.

Even though agent-based models can quite accurately describe the behavior of a population, including the intelligent decision-making by its individuals, large arrays of disparate data are required for the adequacy of the results of experimental studies with such models. The high complexity of the structure of agent-based models often reduces their accuracy. The more data we have about the population and the epidemic process, the more accurately the model will describe the real picture.

The highest accuracy of forecasts is shown by models based on machine learning. Thus, the study [35] built a predictive machine learning model based on the Gaussian process regression method. The model shows high accuracy for both predicting new COVID-19 cases and predicting recoveries. The analysis of models of exponential smoothing, Lasso regression, support vector machine, and linear regression, carried out in [36], showed the highest accuracy in predicting new cases, deaths, and recovery when using a linear regression model.

Moreover, machine learning is used not only to predict the dynamics of the COVID-19 epidemic process. For example, in [37], machine learning methods for predicting the mortality of hospitalized patients with COVID-19 were analyzed using the example of one hospital in Iran. At the same time, it is shown that the random forest model shows the best performance with acceptable accuracy. The review [38] considers machine learning models and methods for predicting the severity of COVID-19 and diagnosing the disease. The results show that most of the models are supervised learning, and the main limitation of the models is the imbalance of the datasets, which is confirmed by inference biases. Review [39] shows applications of machine learning to investigate various aspects of COVID-19. Such aspects include identifying existing medicines, identifying health system risks, and analyzing factors influencing epidemic incidence by age, social habits, location, climate, etc.

Thus, compartmental models are inappropriate for this study since they cannot predict the incidence with sufficient accuracy for the medium and long term. The agent-based approach is also impossible because to build such models, a large amount of disparate data is required, which is impossible to obtain in war conditions. Another popular approach to epidemic processes simulation with high accuracy is neural networks, including deep learning. However, using such models in war conditions is difficult since the use of models in wartime is meant in public health institutions with insufficient computing power and stable Internet access to use cloud services. So, the most appropriate for the task at hand is the use of statistical machine learning methods, which are not only distinguished by their simplicity but also show high accuracy in calculating the predicted morbidity for long periods, which is confirmed not only by the analysis but also by our previous studies [40].

2. Data Analysis

2.1. Background on COVID-19 Pandemic in Ukraine

Before the Russian invasion, Ukraine experienced four waves of COVID-19. The first confirmed case of COVID-19 in Ukraine was registered on March 3, 2020, in the Chernivtsi region. On March 12, 2020, a large-scale quarantine was announced throughout the country, which included the closure of educational institutions and restrictions on public events. The first death from COVID-19 in Ukraine was registered on March 13, 2020. Since March 16, 2020, most checkpoints across the state border have been closed, and entry into the country for foreign citizens has been restricted. The government's harsh restrictive measures at the beginning of the pandemic helped to flatten the incidence curve and prevent the sharp surge that was observed in other countries. The gradual easing of quarantine restrictions began in May 2020.

From the beginning of August 2020, adaptive quarantine was introduced in Ukraine, and epidemic danger levels were set for districts and large cities: green, yellow, orange, and red. However, adaptive quarantine has not been sufficient to contain the incidence and has steadily increased since July 2020. The incidence peaked in November at over 15,000 new cases per day. To reduce the incidence, some measures were introduced - fines for non-compliance with the mask regime on the streets and weekend quarantine, which turned out to be ineffective. However, the incidence began to decline due to the increased number of recovered patients and the isolation of patients. By the end of January 2021, it had decreased to 3000 new cases per day [41].

The second wave of cases began in February 2021 and peaked in April 2021, exceeding 20,000 new cases per day. A new hard lockdown has been introduced. However, new strains of the virus were distinguished by increased virulence, which means that the coronavirus's spread rate increased. In addition to the high incidence, the number of severe forms of COVID-19 has also increased. The occupancy of beds in hospitals exceeded 75%, and in many institutions, there were no places for covid patients at all. In parallel with the increase in the

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incidence in Ukraine, a vaccine campaign against COVID-19 was launched [42].

From September to the end of December 2021, the third wave of COVID-19 was observed in Ukraine, with a peak in early November 2021. The wave is associated with the wide spread of the Delta strain and the low level of vaccination in the population. In addition to record morbidity, the third wave was also characterized by record mortality. Deaths due to COVID-19 exceeded 800 cases per day. Mandatory vaccination of certain groups of the population was introduced, and everyone who received two doses of the vaccine could receive a monetary reward from the state.

Since the beginning of January 2022, the fourth wave of COVID-19 began in Ukraine, associated with the wide spread of the Omicron strain. The new strain has high contagiousness but much lower mortality. At the beginning of the war with Russia on February 24, 2022, the peak of the fourth wave was observed in Ukraine, and the number of new cases reached 30-40 thousand infected daily.

At the beginning of the Russian war in Ukraine, the number of people vaccinated against COVID-19 in Ukraine was 38.24%, and the number of people who received only one dose was 36.96%. While booster doses were actively pursued in Europe, in Ukraine, the percentage of the population who received a booster dose was 1.76%. Children in Ukraine began to be vaccinated only in January 2022, so their number is insignificant [43].

As of February 24, 2022, the number of cases of COVID-19 in Ukraine amounted to 4,809,624 cases. The number of deaths was 105,505 cases [44].

2.2. Impact of the War on the Public Health Facilities in Ukraine

The causeless war that Russia launched in Ukraine on February 24, 2022, became not only a tragedy unprecedented in its scale since World War II but also a global humanitarian catastrophe for Ukraine.

During the first month of the war, the World Health Organization recorded 92 attacks on the Ukrainian healthcare system [45]. 78 attacks were made on medical facilities, 11 on medical transport, including ambulances. A minimum of 73 deaths and 44 injuries have been confirmed due to these attacks. Medical staff suffered from 20 attacks and patients from 11 attacks. 10 attacks affected stocks of medicines, and 2 attacks were made directly on warehouses with medicines. 75 attacks were made using heavy weapons. At the same time, the data used by the Ministry of Health of Ukraine are several times higher.

In Ukraine, about 1,000 medical institutions are located close to active combat zones. Attacks on medical facilities have become part of the strategy and tactics of the war waged by Russia. This is because, first of all, in wartime, assistance is provided to the wounded military and civilians injured due to the war.

Nevertheless, people who need routine medical care, including chronically ill people, also suffer. Because of the war, many distributors of medicines are not working, and the stocks of medicines already existing on the territory of Ukraine are not available or are coming to an end.

The work of medical personnel is problematic in areas where active hostilities are taking place. Part of the personnel from such territories was evacuated. In territories temporarily occupied by Russian troops, the work of medical institutions is often impossible. At the same time, small towns and villages are significantly affected. The destroyed hospitals are the only place for providing medical care within a radius of up to 50 km.

In addition to providing medical care, the war has also disrupted the continuity of Ukraine's healthcare system, which provides critical services to the civilian population. It is difficult to obtain drugs for chronic patients, such as thyroid drugs, insulin for diabetic patients and antiretroviral therapy for HIV-infected people.

In the territories where active hostilities are taking place and, in the territories, temporarily not controlled by Ukraine, the vaccination campaign has been disrupted.

The electronic system of the Ministry of Health of Ukraine, designed to collect information from the regions, operates in a restricted mode. Data from the temporarily occupied territories is not received. It is also challenging to collect information and register patients.

The war also affected the activities carried out to reduce the incidence of COVID-19. According to the changes, which are sent for approval to the Cabinet of Ministers of Ukraine, for the period of martial law, the levels of epidemic danger do not apply to the regions of Ukraine. All restrictive anti-epidemic measures have also been canceled. The rules for the removal from work of unvaccinated employees of those professions for which vaccination against COVID-19 was mandatory to have been canceled.

At the same time, citizens are advised to comply with anti-epidemic measures. However, the psychological state of the citizens of Ukraine pushed the problem of coronavirus into the back.

2.3. Data Sources Analysis

During the COVID-19 pandemic, the Johns Hopkins University & Medicine Coronavirus Resource Center has become the primary source of data for researchers around the world [46]. This initiative has collected and analyzed domestic and international data on COVID-19 since January 22, 2020. However, this dataset is no longer applicable for coronavirus studies in Ukraine because, after February 24, all data on morbidity, mortality, and testing in Ukraine are not available.

Therefore, for this study, we analyzed the WHO Coronavirus (COVID-19) Dashboard of World Health Organization data [44], which coincides with the statistics on coronavirus in Ukraine, which is registered by the Public Health Center under the Ministry of Health of Ukraine. The dashboard provides daily data on COVID-19 cases, deaths, and vaccine use. Data on the incidence of COVID-19 in Ukraine does not include incidence and mortality in the territory of Crimea and the uncontrolled territories of the Donetsk and Lugansk regions as of February 24, 2022. For the accuracy and reliability of the pilot study, all the data used in this article were verified with the official statistics of the Public Health Center under the Ministry of Health of Ukraine.

The statistics reflect laboratory-confirmed cases and reported deaths. All data represent the date of registration, not the onset of symptoms.

3. Materials and Methods

3.1. Methodology

Based on the data on the incidence of COVID-19 in Ukraine, available for analysis during martial law, it is impossible to determine and evaluate the factors that affect the simulated epidemic process. Therefore, within the framework of this study, the problem of forecasting is solved. Based on the results of the analysis of current studies on modeling the epidemic process of COVID-19, carried out in Section 1, as well as from preliminary studies [40], it was concluded that in order to calculate the predicted incidence of COVID-19 in the territory of Ukraine with sufficient accuracy for analysis, it is necessary to apply methods of statistical machine learning. To build a predictive model, the method of polynomial regression is used.

Within the framework of this study, the following methodology is proposed to achieve the set goals:

1. Analyze data on the incidence of COVID-19 in Ukraine, which includes new cases and deaths.
2. Build a machine learning model based on the polynomial regression method to predict the dynamics of the COVID-19 epidemic process.
3. Verify and test the model for adequacy by calculating a retrospective forecast of the incidence of COVID-19 in Ukraine for January 25, 2022, to February 23, 2022 (30 days).
4. Calculate the predicted incidence of COVID-19 in Ukraine for February 24, 2022, to March 25, 2022 (30 days).
5. Calculate the deviations of the predicted incidence from the registered statistics on the incidence of COVID-19 in Ukraine for February 24, 2022, to March 25, 2022 (30 days).
6. Assess the factors influencing the epidemic process of COVID-19 in Ukraine in the conditions of hostilities by analyzing deviations from the point of view of epidemiology.
7. Based on the simulation results, determine the public health risks and necessary measures to reduce the incidence of COVID-19 in Ukraine in the context of hostilities.

3.2. Polynomial Regression Model

Regression analysis is a set of statistical methods for evaluating relationships between variables. Regression methods can be used to estimate the degree of relationship between variables and to model future dependencies. Regression analysis shows how changes in the independent variables can be used to fix the change in the dependent variable.

Polynomial regression is used to model the trend components of a time series [47].

Let two series of observations x_i and y_i be given. Then the polynomial equation has the following form:

$$y = \sum_{j=0}^{k} b_j x^j, \tag{1}$$

where b_j are the parameters of this polynomial;

$j = \overline{0, k}$;

b_0 is free term.

Let's find the regression parameters b_j using the least squares method:

$$S = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \to \min, \tag{2}$$

where $\hat{y}_i$ are the values of polynomial (1) at the points x_i.

Let's substitute (1) into (2), and get:

$$S = \sum_{i=1}^{n} \left(\sum_{j=0}^{k} b_j x_i^j - y_i \right)^2 \to \min. \tag{3}$$

Satisfying the necessary condition for the extremum of the function (k + 1) of variables $S = S(b_0, b_1, \dots, b_k)$, one should equate its partial derivatives to zero:

$$S'_{b_p} = 2 \sum_{i=1}^{n} x_i^p \left(\sum_{j=0}^{k} b_j x_i^j - y_i \right) = 0, \tag{4}$$

where $p = \overline{0, k}$.

Simplifying equation (2), obtain

$$\sum_{i=1}^{n} x_i^p \left(b_0 + b_1 x_i + b_2 x_i^2 + \dots + b_k x_i^k \right) - \sum_{i=1}^{n} x_i^p y_i = 0. \tag{5}$$

As a result, we obtain (k + 1) expressions that form

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a system of linear equations with respect to b_p, which has the following form:

$$A = \begin{pmatrix} 1 & \overline{x} & \overline{x^2} & \dots & \overline{x^k} \\ \overline{x} & \overline{x^2} & \overline{x^3} & \dots & \overline{x^{k+1}} \\ \overline{x^2} & \overline{x^3} & \overline{x^4} & \dots & \overline{x^{k+2}} \\ \dots & \dots & \dots & \dots & \dots \\ \overline{x^k} & \overline{x^{k+1}} & \overline{x^{k+2}} & \dots & \overline{x^{2k}} \end{pmatrix}, \quad (6)$$

$$B = \begin{pmatrix} b_0 \\ b_1 \\ b_2 \\ \dots \\ b_k \end{pmatrix}, C = \begin{pmatrix} \overline{y} \\ \overline{xy} \\ \overline{x^2y} \\ \dots \\ \overline{x^ky} \end{pmatrix}. \quad (7)$$

Let a time series x_t be given, where $t = \overline{1, n}$. It is necessary to build a polynomial trend of order k, which approximates the time series with the greatest accuracy. The independent variable x is t. y are the values of the time series x_t, i.e. the number of new cases or deaths of COVID-19. Then the value a_{ij} of matrix A will look like:

$$a_{ij} = \frac{1}{n}\sum_{r=1}^{n} r^{i+j-2}, \quad (8)$$

where $i, j = \overline{1, (k+1)}$.

The elements c_j of the matrix of free terms have the following form:

$$c_j = \frac{1}{n}\sum_{r=1}^{n} r^{j-1} x_r, \quad (9)$$

where $j = \overline{1, (k+1)}$.

Thus, solving the system of equations (6), (7), we find the desired parameters of the polynomial trend $b_0, \dots, b_k$. As a result, the trend component will look like:

$$T_t = \sum_{i=0}^{k} b_i t^i. \quad (10)$$

3.3. Model Verification Methods

The model accuracy estimate is calculated using mean absolute percentage error:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \quad (11)$$

where A_t is the actual value;

F_t is the forecasted value.

To assess the forecast of the incidence of COVID-19 for the period of the war, the deviations of the forecast data from the registered statistics were calculated:

$$D = |F_t - A_t|, \quad (12)$$

where A_t is the actual value; F_t is the forecasted value.

4. Results

4.1. Model Verification

A machine learning model based on the polynomial regression method for predicting the epidemic process of COVID-19 was implemented in Python. Figure 1 shows the results of retrospective forecasting of cumulative new cases of COVID-19 in Ukraine from January 25, 2022, to February 23, 2022. Forecasts were calculated for 7, 10, 20, and 30 days to illustrate the change in the forecast error with the increasing period.

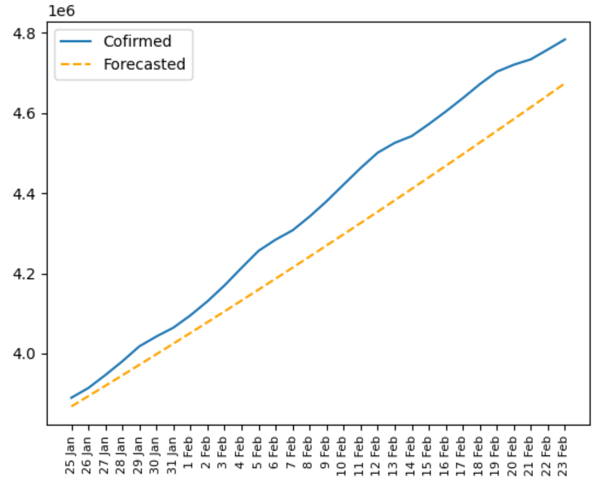

Fig. 1. Forecasting of COVID-19 cumulative new cases (25.01.22 – 23.02.2022)

Figure 2 shows a retrospective forecast of death cases of COVID-19 in Ukraine from January 25, 2022 to February 23, 2022.

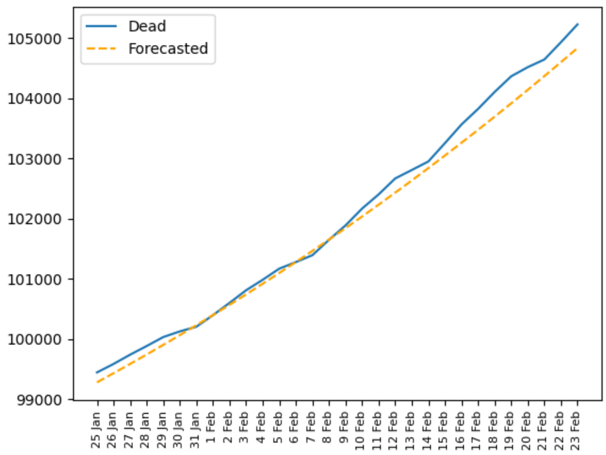

Fig. 2. Forecasting of COVID-19 cumulative death cases (25.01.22 – 23.02.2022)

Table 1 shows model accuracy rates for cumulative new cases and deaths of COVID-19 in Ukraine for a sample from January 25, 2022 to February 23, 2022.

Table 1

MAPE of forecast for 25.01.22 – 23.02.22 (%)

Duration of forecast (days)	New cases	Death cases
7 days	0,83732 %	0,11900 %
10 days	0,97512 %	0,09342 %
20 days	1,77691 %	0,09431 %
30 days	2,12166 %	0,16542 %

As the prediction results show, our hypothesis about the high accuracy of simple statistical machine learning models was confirmed. Forecast accuracy is sufficient for a long-term forecast of 30 days for both new and death cases.

4.2. COVID-19 Epidemic Process Estimation during War

To assess the epidemic process of COVID-19 in Ukraine during the war, we applied the developed model to a sample of new cases and deaths of COVID-19 to build a forecast from February 24, 2022, to March 25, 2022. Figure 3 shows the forecast of cumulative new cases of COVID-19 in Ukraine, along with the reported new cases for the period from February 24, 2022, to March 25, 2022.

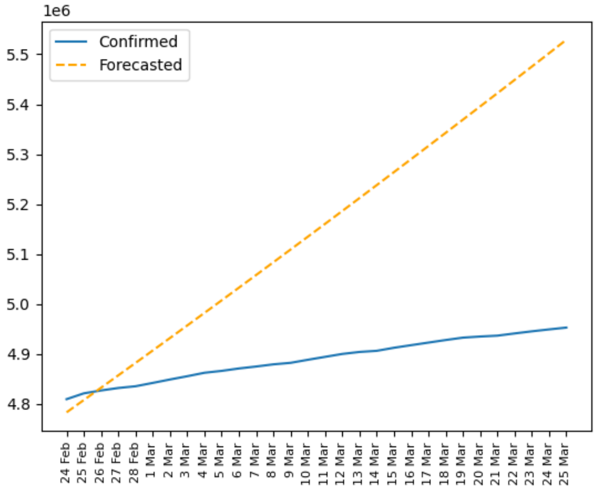

Fig. 3. Forecasting of COVID-19 cumulative new cases (24.02.22 – 25.03.2022)

Figure 4 shows the forecast of cumulative death cases of COVID-19 in Ukraine, along with the reported new cases for the period from February 24, 2022, to March 25, 2022.

Figure 5 shows the forecast of daily new cases of COVID-19 in Ukraine, along with the reported new cases for the period from February 24, 2022, to March 25, 2022.

Figure 6 shows the forecast of daily death cases of COVID-19 in Ukraine, along with the reported new cases for the period from February 24, 2022, to March 25, 2022.

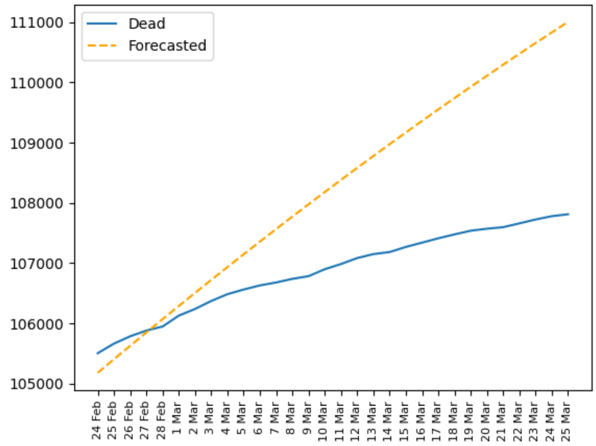

Fig. 4. Forecasting of COVID-19 cumulative death cases (24.02.22 – 25.03.2022)

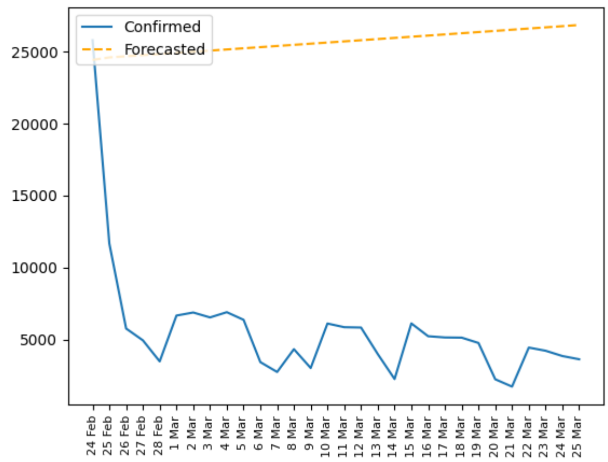

Fig. 5. Forecasting of COVID-19 daily new cases (24.02.22 – 25.03.2022)

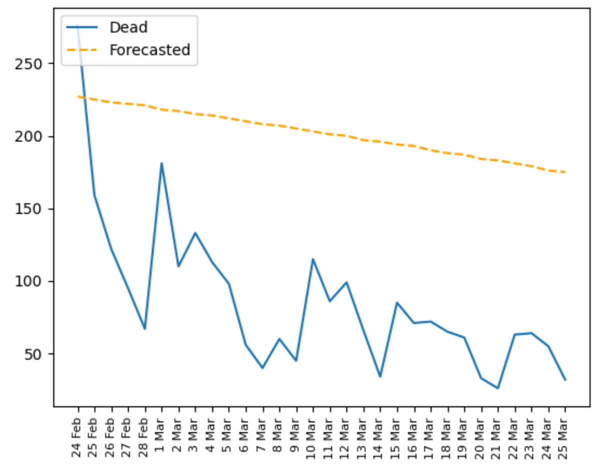

Fig. 6. Forecasting of COVID-19 daily death cases (24.02.22 – 25.03.2022)

Table 2 shows forecast accuracy rates for daily new cases and deaths of COVID-19 in Ukraine for a sample from February 24, 2022, to March 25, 2022.

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Table 2

MAPE of forecast for 24.02.22 – 25.03.22 (%)

Duration of forecast (days)	New cases	Death cases
7 days	285,07129 %	89,04280 %
10 days	283,96430 %	89,06608 %
20 days	423,01236 %	165,08350 %
30 days	497,08910 %	204,28213 %

An assessment of the forecast for the wartime period shows that the registered statistics regarding COVID-19 in Ukraine do not reflect the actual situation.

Figure 7 shows the deviation of daily reported new cases of COVID-19 in Ukraine from the predicted values for the period from February 24, 2022, to March 25, 2022.

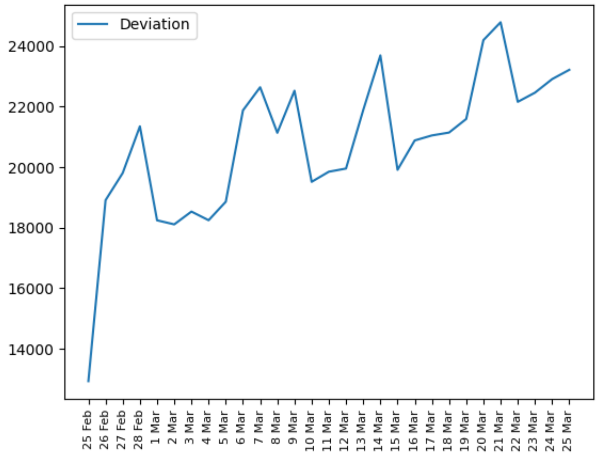

Fig. 7. Deviation of COVID-19 daily new cases from predicted values (24.02.22 – 25.03.2022)

Figure 8 shows the deviation of daily reported death cases of COVID-19 in Ukraine from the predicted values for the period from February 24, 2022, to March 25, 2022.

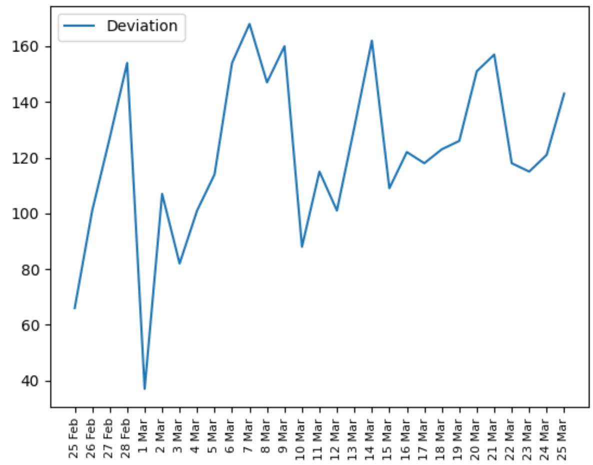

Fig. 8. Deviation of COVID-19 daily death cases from predicted values (24.02.22 – 25.03.2022)

5. Discussion

The challenges for the global community and public health associated with the COVID-19 pandemic have forced us to look for ways to reduce the incidence and deaths of the population using different approaches and tools. The results of the COVID-19 epidemic process mathematical modeling made a significant contribution to managerial decision-making, which on the one hand, were aimed at developing the most effective preventive and anti-epidemic measures [48, 49], on the other hand, at a better understanding of the development and dynamics of the epidemic process [50-53].

COVID-19 is an emerging infection with an aerosol transmission mechanism. The source of infection is a sick person or carrier. The manifestations of the epidemic process are primarily associated with the ease of implementation of the transmission mechanism. Shedding of the pathogen from the body of the source of infection occurs during forced expiration - coughing, sneezing, loud talking, screaming. The causative agent emission the air in the form of an aerosol and penetrates the susceptible organism during the physiological act of inhalation [54]. The higher the concentration of the pathogen in the inhaled air, the higher the likelihood of infection in a susceptible person. Therefore, the risks of infection with the SARS-CoV-2 virus increase dramatically in poorly ventilated rooms. There are many people among whom there is a high probability of a source of infection [55]. It should be borne in mind that the identification and subsequent isolation of the source of infection is always a belated event, which is associated with the presence of the incubation period of the disease when there are no clinical symptoms yet, and the pathogen is already being isolated; with the presence of mild forms of the course of the disease, when a sick person ignores the symptoms, with the presence of carriage – cases when there are no symptoms, and the pathogen is isolated [56-58]. These features allow the virus to spread rapidly among people, in closed groups, in crowded conditions. The pandemic also revealed the variability of the virus as it adapts to the human body. New variants of the pathogen appeared, which led to repeated cases of infection and a further increase in the incidence.

On the eve of the day when the Russian Federation treacherously and brutally unleashed a war with Ukraine, on February 23, 2022, 4 783 835 cases of COVID-19 and 105 229 deaths due to this disease were registered in the country, the daily incidence was 25 062 cases, and the death rate was 276 cases. In the dynamics of the epidemic process, an increase in the incidence was noted with the dominance of the Omicron variant, which is characterized by easier transmissibility [59-60]. The forecast constructed using a polynomial regression model, which showed high accuracy (97,88% when forecasting for 30 days), showed a further increase in the incidence.

However, studying the manifestations of the epidemic process during the first month of the war showed that the registered incidence of COVID-19 in Ukraine was significantly lower than the calculated indicators, which indicates the presence of a hidden component of the COVID-19 epidemic process. For the timely and rational implementation of effective anti-epidemic and preventive measures in the circumstances of war and limited resources, it is essential to understand the causes and conditions for the formation of a hidden component of the epidemic process, how much the actual morbidity and mortality differ from the registered one in order to avoid significant deterioration of the epidemic situation, the occurrence of severe cases of the disease that require oxygen, resulting in an even more significant strain on an already war-torn health care system.

An analysis of the current situation in the conditions of the war in Ukraine showed that, along with significant destruction, deaths, and injuries due to the use of various types of weapons by the aggressor, a humanitarian crisis has developed in the occupied territories and territories where hostilities are taking place, which has affected all aspects of people's lives, including access to health care. The health sector suffered under the conditions of the war. Only in one city of Kharkiv, 75% of health care facilities were destroyed or damaged. The capacity of the laboratory base decreased, which led to a decrease in the volume of testing and, accordingly, the diagnosis and registration of cases of Covid-19. Nevertheless, the number of people with symptoms of COVID-19 seeking medical help has also decreased, which is explained by the closure of many medical institutions in the territories where hostilities are taking place, the lack of communication (telephone, Internet) for contacting a doctor, ignoring the symptoms that have appeared, because all the attention of the sick person is drawn only to the events connected with the war. Low detection and under-reporting of cases lead to the fact that contacts are not traced and isolated, and many active sources of infection are formed.

At the same time, with the outbreak of war treacherously and brutally unleashed by Russia against Ukraine, the problems caused by the pandemic have worsened. Military operations have led to significant destruction, the destruction of life-supporting infrastructure in many settlements. Conditions have been created in Ukraine to intensify the epidemic process of COVID-19. Bomb attacks, rocket attacks, artillery, and mortar attacks forced people to leave their homes and areas of active hostilities where they previously lived. There is a very high crowding of people at stations, in trains, places of temporary residence of internally displaced persons, a lack of elementary sanitary conditions, and sufficient air exchange. There are no conditions for maintaining social distance. People do not adhere to the policy of wearing masks. There is no quarantine and isolation of patients. This creates conditions for the intensification of the circulation of the pathogen. Increased migration of the population and flows of displaced persons contribute to introducing new variants of coronavirus into other territories. The situation is complicated by the lack of a protective level of immunity against COVID-19 in most of the population. Even though scientists quickly developed effective vaccines for the prevention of COVID-19, which began to be used in Ukraine from the end of February 2021, by the beginning of hostilities in Ukraine, vaccination coverage of the population was low, children under 12 years of age were not subject to vaccination at all and vaccination coverage among adolescents was low. All this does not effectively contain the spread of the virus.

Thus, with the start of hostilities in Ukraine, conditions were created to activate the COVID-19 epidemic process. The development of the epidemic process included additional factors that increased the spread of infection, which were not present when constructing the morbidity forecast. For this reason, it would be expected that the actual incidence would exceed the predicted one, which we did not observe.

The obtained simulation results highlighted some of the existing problems and made it possible to draw lessons for the further functioning of healthcare systems in extreme conditions, including during war. Modeling is necessary to assess the dynamics of the epidemic process under constantly existing conditions and factors affecting the incidence to make timely adjustments to the structure and scope of preventive and anti-epidemic measures that hinder the development of a pandemic. In the context of the weakening of the epidemiological surveillance and response systems, when changing conditions worsen the epidemic situation, mathematical modeling and the use of adequate models make it possible to eliminate or minimize the consequences of a disruption in the work of public health structures and adjust the activities of relevant services and avoid additional burden on the healthcare system associated with a growing incidence, disease severity, and mortality.

It should be emphasized the need and expediency of broad cooperation between model developers and decision-makers, the importance of a strategic partnership to ensure epidemic well-being and national security in curbing the spread of infectious diseases.

Conclusions

The paper describes the results of a pilot study to assess the incidence of COVID-19 in Ukraine during the war. A machine learning model was built based on the polynomial regression method for forecasting. The simulation used cumulative and daily data on new cases and

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deaths of COVID-19 in Ukraine from January 25, 2022, to March 25, 2022, posted in the World Health Organization Dashboard.

The scientific novelty of the study lies in the development and study of a machine learning model of the epidemic process of an emergent disease using the example of COVID-19, based on the polynomial regression method. This allows the model to assess the epidemic situation for a long-term period (30 days). Unlike existing studies, the forecast accuracy obtained using the constructed model was evaluated both for new cases of morbidity and for death cases. The assessment was carried out for various forecasting periods.

The practical novelty of the study lies in the assessment of the epidemic situation associated with COVID-19 on the territory of Ukraine during military operations. The simulation tool is exceptionally relevant during the war because it does not incur high costs of financial, human, and time resources; other tools for assessing the epidemic situation in war conditions are unavailable, limited, or their capacities are redistributed to solve other tasks.

The constructed model showed sufficient accuracy in predicting both new and death cases of COVID-19 for the effectiveness of its use in practice. The hindcast showed an accuracy of 97,88% when modeling new cases and 99,83% when modeling death cases of COVID-19. Simulation of the epidemic process of COVID-19 for the first month of Russia's war in Ukraine showed a significant deviation of the predicted incidence from the recorded one.

The significant deviation is since the registration of morbidity and death from COVID-19 in wartime conditions is difficult. Data collection and transmission are impossible in areas where active hostilities are taking place and in temporarily occupied territories.

In addition, high population density during the evacuation from dangerous areas and when staying in bomb shelters contribute to the spread of COVID-19. The high psychological stress of people in the conditions of hostilities contributes to non-compliance with anti-epidemic measures even in territories where hostilities are not conducted.

Thus, as the modeling results show, most of the incidence of COVID-19 in Ukraine in wartime conditions remains outside the statistics. This creates new challenges for the public health system. At the same time, the main recommendation is the observance by the population of anti-epidemic measures, such as observance of the mask regime, if possible, booster vaccination, despite the abolition of mandatory compliance with such measures at the legislative level.

Future research development. A high percentage of unreported COVID-19 statistics in Ukraine related to Russia's military intervention on the territory of Ukraine poses new challenges for healthcare systems not only in Ukraine but also in countries that accept a large number of refugees from Ukraine. Thus, the high density of people during the evacuation is a stimulating factor in the spread of both COVID-19 and other infectious diseases. At the same time, the period for starting the evacuation and reaching the final destination is often less than the incubation period. This creates the risk of outbreaks of infectious diseases in the countries of the European Union, which have accepted the most significant number of refugees. Simulation modeling is an effective tool to assess the risks and effectiveness of anti-epidemic measures aimed at suppressing such outbreaks.

Contributions of authors: conceptualization – **D. Chumachenko, T. Chumachenko**; methodology – **D. Chumachenko**; formulation of tasks – **D. Chumachenko, I. Meniailov**; analysis – **D. Chumachenko, P. Pyrohov, I. Meniailov, T. Chumachenko**; development of model – **D. Chumachenko, P. Pyrohov, I. Meniailov**; software – **P. Pyrohov, I. Meniailov**; verification – **D. Chumachenko, T. Chumachenko**; analysis of results – **D. Chumachenko, T. Chumachenko**; visualization – **P. Pyrohov, I. Meniailov**; writing – original draft preparation – **D. Chumachenko, T. Chumachenko**; writing – review and editing – **P. Pyrohov, I. Meniailov**. All the authors have read and agreed to the published version of the manuscript.

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ВПЛИВ ВІЙНИ НА ПАНДЕМІЮ COVID-19 В УКРАЇНІ: РЕЗУЛЬТАТИ МОДЕЛЮВАННЯ

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Пандемія нової коронавірусної інфекції COVID-19 стала викликом для систем охорони здоров'я всього світу. На березень 2022 року у світі зареєстровано майже 500 мільйонів випадків. Понад 6,2 мільйона людей загинули. Війна, яку безпричинно розпочала Росія на території України, є не лише причиною загибелі тисяч людей та руйнування десятків міст, а й масштабною гуманітарною кризою. Також військове вторгнення торкнулося і сфери охорони здоров'я. Неможливість надання медичної допомоги, недотримання санітарних умов на територіях, на яких ведуться активні бойові дії, висока щільність населення під час евакуації, а також інші фактори, сприяють новому етапу поширення COVID-19 в Україні. Побудова адекватної моделі епідемічного процесу дозволить оцінити реальну статистику захворюваності на COVID-19, а також оцінити ризики та ефективність заходів щодо стримування епідемічного розвитку хвороби. **Метою** статті є розробка імітаційної моделі епідемічного процесу COVID-19 в Україні та дослідження результатів експериментального дослідження в умовах війни. **Об'єкт дослідження** – епідемічний процес COVID-19 у воєнних умовах. **Предмет дослідження** – моделі та методи моделювання епідемічного процесу, що базуються на методах статистичного машинного навчання. Для досягнення мети дослідження ми використали **методи** прогнозування та побудували модель епідемічного процесу COVID-19 на основі методу поліноміальної регресії. В **результаті** експериментів точність прогнозування на 30 днів нових випадків COVID-19 в Україні склала 97,98 %, летальних випадків COVID-19 в Україні – 99,87 %. Модель застосована до даних із захворюваності COVID-19 в Україні за перший місяць війни (24.02.22 – 25.03.22). Розраховані прогнозні значення виявили значне відхилення від зареєстрованої статистики. **Висновки.** У статті описано експериментальні дослідження реалізації моделі епідемічного процесу COVID-19 в Україні на основі методу поліноміальної регресії. Побудована модель має достатню точність для прийняття рішень щодо проведення протиепідемічних заходів щодо боротьби з пандемією COVID-19 на вибраній території. Дослідження моделі на даних про захворюваність на COVID-19 в Україні під час війни дозволило оцінити повноту статистики, що реєструється, виявити ризики поширення COVID-19 у воєнний час, а також визначити необхідні заходи для стримування епідемічного розповсюдження захворюваності на COVID-19 в Україні. Вивчення результатів експериментального дослідження показує значне зниження реєстрації захворюваності на COVID-19 в Україні. Аналіз ситуації показав утруднення доступу до медичного обслуговування, зниження діагностики та реєстрації нових випадків, а війна призвела до активізації епідемічного процесу COVID-19.

Ключові слова: епідемічна модель; епідемічний процес; моделювання епідемії; моделювання; COVID-19; поліноміальна регресія, війна.

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Пандемия новой коронавирусной инфекции COVID-19 стала вызовом для систем общественного здравоохранения всего мира. На март 2022 года в мире зарегистрировано почти 500 миллионов случаев. Более 6,2 миллионов людей погибли. Война, которую беспричинно начала Россия на территории Украины является не только причиной гибели тысяч людей и разрушения десятков городов, но и масштабным гуманитарным кризисом. Также военное вторжение затронуло и сферу общественного здравоохранения. Невозможность оказания медицинской помощи, несоблюдение санитарных условий на территориях, на которых ведутся активные боевые действия, высокая плотность населения при эвакуации, а также другие факторы способствуют новому этапу распространения COVID-19 в Украине. Построение адекватной модели эпидемического процесса позволит оценить реальную статистику заболеваемости COVID-19, а также оценить риски и эффективность мероприятий по сдерживанию эпидемического развития болезни. **Целью** статьи является разработка имитационной модели эпидемического процесса COVID-19 в Украине, и исследование результатов экспериментального исследования в условиях войны. **Объект исследования** – эпидемический процесс COVID-19 в военных условиях. **Предмет исследования** – модели и методы моделирования эпидемического процесса, основанные на методах статистического машинного обучения. Для достижения цели исследования мы использовали **методы** прогнозирования и построили модель эпидемического процесса COVID-19 на основе метода полиномиальной регрессии. В **результате** экспериментов, точность прогнозирования на 30 дней новых случаев COVID-19 в Украине составила 97,98 %, летальных случаев COVID-19 в Украине – 99,87 %. Модель применена к данным по заболеваемости COVID-19 в Украине за первый месяц войны (24.02.22 – 25.03.22). Рассчитанные прогнозные значения показали значительное отклонение от зарегистрированной статистики. **Выводы.** В статье описаны экспериментальные исследования реализации модели эпидемического процесса COVID-19 в Украине на основе метода полиномиальной регрессии. Построенная модель обладает достаточной точностью для принятия решений о проведении противоэпидемических мероприятий по борьбе с пандемией COVID-19 на выбранной территории. Исследование модели на данных о заболеваемости COVID-19 в Украине во время войны позволило оценить полноту регистрируемой статистике, выявить риски распространения COVID-19 в военное время, а также определить необходимые мероприятия для сдерживания эпидемического развития заболеваемости COVID-19 в Украине. Изучение результатов экспериментального исследования показывает значительное снижение регистрации заболеваемости COVID-19 в Украине. Анализ ситуации показал затруднение к доступу к медицинскому обслуживанию, снижению диагностики и регистрации новых случаев, а война привела к активизации эпидемического процесса COVID-19.

Ключевые слова: эпидемическая модель; эпидемический процесс; моделирование эпидемии; моделирование; COVID-19; полиномиальная регрессия; война.

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