D. CHUMACHENKO[1], I. MENIAILOV[1], A. HRIMOV[1], V. LOPATKA[1], O. MOROZ[2], O. TOLSTOLUZKA[2]

[1] *National Aerospace University "Kharkiv Aviation Institute", Ukraine*
[2] *V. N. Karazin Kharkiv National University, Ukraine*

SIMULATION AND FORECASTING OF THE INFLUENZA EPIDEMIC PROCESS USING SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL

*Today's global COVID-19 pandemic has affected the spread of influenza. COVID-19 and influenza are respiratory infections and have several similar symptoms. They are, however, caused by various viruses; there are also some differences in the categories of people most at risk of severe forms of these diseases. The strategies for their treatment are also different. Mathematical modeling is an effective tool for controlling the epidemic process of influenza in specified territories. The results of modeling and forecasts obtained with the help of simulation models make it possible to develop timely justified anti-epidemic measures to reduce the dynamics of the incidence of influenza. The study aims to develop a seasonal autoregressive integrated moving average (SARIMA) model for influenza epidemic process simulation and to investigate the experimental results of the simulation. The work is targeted at the influenza epidemic process and its dynamic in the territory of Ukraine. The **subjects** of the research are methods and models of epidemic process simulation, which include machine learning methods, in particular the SARIMA model. To achieve the aim of the research, we have used **methods** of forecasting and have built the influenza epidemic process SARIMA model. Because of experiments with the developed model, the predictive dynamics of the epidemic process of influenza for 10 weeks were obtained. Such a forecast can be used by persons making decisions on the implementation of anti-epidemic and deterrent measures if the forecast exceeds the epidemic thresholds of morbidity. **Conclusions.** The paper describes experimental research on the application of the SARIMA model to the epidemic process of influenza simulation. Models have been verified by influenza morbidity in the Kharkiv region (Ukraine) in epidemic seasons for the time ranges as follows: 2017-18, 2018-19, 2019-20, and 2020-21. Data were provided by the Kharkiv Regional Centers for Disease Control and Prevention of the Ministry of Health of Ukraine. The forecasting results show a downward trend in the dynamics of the epidemic process of influenza in the Kharkiv region. It is due to the introduction of anti-epidemic measures aimed at combating COVID-19. Activities such as wearing masks, social distancing, and lockdown also contribute to reducing seasonal influenza epidemics.*

Keywords: epidemic model; epidemic process; epidemic simulation; simulation; SARIMA model; influenza.

Introduction

Influenza is an acute viral infection that spreads easily from person to person. The flu circulates around the world, causing epidemics and affecting people of all ages. In addition to seasonal epidemics, the emergence of a new subtype of influenza virus can provoke influenza pandemics. Influenza affects primarily the upper respiratory tract, including the nose and throat, as well as the bronchi, less often the lungs. The disease occurs all over the world and spreads very quickly among the population, especially in crowded places. Influenza epidemics occur annually in the Northern Hemisphere in autumn and winter, during which the infection affects approximately 5…15 % of the population [1].

Influenza is characterized by the acute development of symptoms such as a sharp increase in body temperature, cough, headache, muscle and joint pain, malaise, runny nose, and lasts from 2 to 7 days. Influenza usually manifests itself in mild, uncomplicated form, and in most cases, infected people recover without any specific treatment. However, influenza infection can sometimes cause serious illness and death, especially among the elderly, pregnant women, young children, and people with certain health conditions (including chronic diseases of the heart, lungs, kidneys, liver, blood, with metabolic disorders, with a weakened immune system) [2].

Influenza epidemics, be they mild, moderate, or severe, affect a large portion of the population, placing significant strain on the health care system and other essential services, and can lead to significant economic losses. Because an influenza epidemic can last for months or even years, the health sector, as well as other sectors providing basic services such as energy and food production, must respond systematically [3]. For this reason, countries create multi-sectoral preparedness plans that

describe the strategy and operational plans for responding to an epidemic.

Today's global COVID-19 pandemic has affected the spread of influenza [4]. COVID-19 and influenza are respiratory infections and have many similar symptoms. They are, however, caused by various viruses; there are also some differences in the categories of people most at risk of severe forms of these diseases. The strategies for their treatment are also different.

Both infections, COVID-19 and influenza, are transmitted by droplets or aerosols released by an infected person when they cough, sneeze, speak, sing, or breathe. Drops and aerosols can get into the eyes, nasopharynx, or mouth of people around, usually, if they are less than 1 m from the infected person, but sometimes even further. You can also get COVID-19 and influenza by touching contaminated surfaces and then touching your eyes, nose, or mouth with unwashed hands. This means that the measures to counter the increase in the incidence are similar for influenza and COVID-19. The active fight against the COVID-19 pandemic has led to a decrease in the incidence of illness and influenza [5], however, on the other hand, all forces today are concentrated on the fight against the coronavirus, and the fight against the spread of influenza has receded into the background [6].

Also, the importance of introducing measures against the incidence of influenza is dictated by the increased likelihood of death with the simultaneous illness of influenza and COVID-19 [7].

In Ukraine, the incidence of influenza and acute respiratory viral infections is seasonal. The epidemic season is counted from 41 to 13 weeks [8]. Morbidity data are recorded only during epidemic seasons. Even though 1.25 million doses of influenza vaccines are planned for the epidemic season 2021-22, the level of immunization of the population is low and insufficient to prevent an epidemic from emerging [9]. During the epidemic season 2020-2021, 13.1 % of the country's population fell ill with influenza and acute respiratory viral infections, 147,232 people were hospitalized, of which 24.1 % were children under 17 years old, no deaths due to influenza were recorded [10].

The paper aims to develop a seasonal autoregressive integrated moving average (SARIMA) model for influenza epidemic process simulation and to investigate the experimental results of the simulation. The research is targeted at the influenza epidemic process. The subjects of research are methods and models of epidemic process simulation, which includes machine learning methods, in particular the SARIMA model.

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

1. Methods and models of the influenza epidemic process should be analyzed.

2. SARIMA model of influenza epidemic process based on linear regression method should be developed.

3. Data on influenza morbidity in Ukraine should be prepared for model application.

4. Experimental evaluation of the SARIMA model of the influenza epidemic process should be provided.

5. 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 SARIMA approach will allow estimating the accuracy of simple machine learning methods applied to the simulation of the epidemic process. Secondly, the application of the SARIMA model to the influenza epidemic process in Ukraine will allow estimating its dynamics.

In this paper, section 1, namely the current research analysis provides the current state of influenza simulation methods and models. Section 2, namely materials and methods, provides a brief overview of moving average, autoregressive, autoregressive integrated moving average, seasonal autoregressive integrated moving average approaches, and developed methods of data preprocessing and preparation. Section 3 provides the results of data preparation, preprocessing, and stationing. Also, the forecasting of influenza morbidity dynamics in the Kharkiv region (Ukraine) is done. Conclusions describe the outcomes of the proposed methodology.

Given research is part of a complex intelligent information system for epidemiological diagnostics, the concept of which is discussed in [11].

1. Current Research Analysis

Methods of mathematical modeling have been developed for over 100 years. Among the models of influenza and acute respiratory viral diseases, one can single out the study of Rvachev [12], who, using classical compartment models, simulated the spread of influenza in the USSR in the middle of the XX century.

Other scientists have also used the apparatus of systems of differential equations to model the incidence of influenza. In paper [13] classical Susceptible–Infected–Recovered (SIR) model has been extended with assumptions that the magnitude of transmission does not vary between influenza A and B. The model has been applied to Israel dataset regarding influenza morbidity. Authors of [14] proposed to extend the SIR model to higher dimensions, allowing the modeling of a population infected by multiple viruses. The proposed model was applied to a five-year seasonal influenza-like illness rate, estimated from Twitter data. Paper [15] proposes a multi-strain SIR epidemic model with selective immunity by vaccination. Authors assume that the newer strain does not exhibit cross-immunity with the original strain, hence those who

are vaccinated and recovered from the original strain become susceptible to the newer strain. Paper [16] proposes an extended SIR model for analysis of the transmission dynamics of influenza A virus having incorporated the aspect of drug resistance. Numerical simulations reveal that despite vaccination reducing the reproduction number below unity, influenza persists in the population. Paper [17] describes a parametric bootstrap approach to generate simulated data from dynamical systems to quantify parameter uncertainty and identifiability with application to low-complexity SEIR model of influenza, Ebola, and Zika pandemics.

The main disadvantage of classical compartment models based on systems of differential equations is the complexity of making changes to the model. When the virulence of the virus changes, the infectivity index increases, and the population groups most susceptible to infection change. Also, the introduction of preventive measures to reduce the dynamics of morbidity affects the rules for the spread of the virus. To take into account the dynamically changing parameters of the system of differential equations, it is necessary to build anew, which leads to untimely decision-making regarding control anti-epidemic measures. These drawbacks can be eliminated by using statistical and machine learning methods of epidemic process simulation.

The authors of [18] applied a 3-weeks moving average model to investigate the seasonal dynamics of influenza in the WHO European Region. The authors of the paper [19] applied an exponentially weighted moving average method to detect the start of influence outbreak in Viktoria, Australia. Paper [20] investigates the effectiveness of the application of the exponentially weighted moving average method to timely detection of influenza outbreaks in Iran. Paper [21] describes the regressive integrated moving average model based on surveillance data from Google Trends on influenza morbidity to forecast type-specific seasonal influenza. In [22, 23] the autoregressive moving average model has been proposed to investigate the dynamics of influenza.

The disadvantage of the proposed methods is that they do not take into account the seasonal dynamics of the epidemic process. The application of artificial intelligence-based methods and models are popular approaches to analysis the dynamical systems, in particular in healthcare: for prediction tasks [24], small data analysis [25], data openness estimation [26], simulation modeling [27], healthcare information systems integration [28], medical diagnostics [29], development of intelligent systems [30], etc. But due to the representation of morbidity data in Ukraine as a time-series that methods are hard to implement in the current task. This study proposes the development of a SARIMA model for predicting the dynamics of influenza in Ukraine.

2. Models and Methods

2.1. Simple Moving Average

Moving average belongs to the class of trend-following indicators, it helps to determine the beginning of a new trend and its end, its slope angle can be used to determine the strength (speed of movement), it is also used as a basis (or a smoothing factor) in a large number of other technical indicators [31]. Sometimes a moving average is called a trend line.

$$SMA = \frac{\sum\limits_{i=1}^{n} P_i}{n},\qquad(1)$$

where P_i is the value of time series, n is the smoothing length or moving average period.

Moving averages will not predict changes in the trend, but will only signal an already emerging trend. Since moving averages are trend-following indicators, it is better to use them during trend periods, and when the trend is not present in the process under study, they become completely ineffective. Therefore, before using these indicators, it is necessary to conduct a separate analysis of the trend properties of specific values of the time series.

2.2. Autoregressive Model

An autoregressive model is a time series model in which its current value linearly depends on the previous values of the same series [32]. Linear relationship means that the current value is equal to the weighted sum of several previous values in the series

$$Y(t) = C + \sum\limits_{i=1}^{n} b_i Y_{t-n} + \varepsilon_t,\qquad(2)$$

where C is a constant, which for simplicity is often assumed to be 0; n is the number of retrospective values of the series taken into account in the model (the order of the model); b_i are coefficients (parameters) of the model that need to be estimated when building it; ε_t is a random component reflecting the probabilistic nature of the model.

Thus, knowing the parameters of the model and the corresponding retrospective values of the time series, we can predict its future values.

2.3. Autoregressive Integrated Moving Average Model

The Autoregressive Integrated Moving Average Model (ARIMA) is a time series forecasting method created by regressing the dependent variable only on its lag

value and the current value and lag value of the random error term in the process of converting non-stationary time series to stationary time series [33].

The model treats the sequence of data generated by the predicted object over time as a random sequence and uses a mathematical model to describe this sequence. Once the model is identified, the future values of the time series can be predicted from the past and current values of the time series.

The autoregressive model with integration and moving average of orders (p, d, q) is the sum of the autoregressive model from the past values of p periods and the moving average model of the previous q periods, and can be represented as

$$\Delta^d X_t = C + \sum_{i=1}^{p} a_i \Delta^d X_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t, \qquad (3)$$

where ε_t is stationary time series; c, a_i, b_j are parameters of the model; Δ^d is the operator of the difference of the time series of order d (sequential taking of d times of the differences of the first order - first from the time series, then from the obtained differences of the first order, then from the second order, etc.)

ARIMA's approach to time series is that the stationarity of the series is assessed first. Various tests reveal the presence of unit roots and the order of integration of the time series. Further, if necessary, the series is transformed by taking the difference of the corresponding order, and already for the transformed model, a certain ARIMA model is constructed, since it is assumed that the resulting process is stationary, in contrast to the original non-stationary process.

The problem with ARIMA is that it doesn't support seasonal data. This is a time series with a repeating cycle.

2.4. Seasonal Autoregressive Integrated Moving Average Model

Seasonal Autoregressive Integrated Moving Average (SARIMA) method for forecasting time series with univariate data containing trends and seasonality is an ARIMA extension that supports direct modeling of the seasonal component of the series [34].

It adds three new hyperparameters for specifying autoregressive (AR), integrated (I), and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the seasonality period. The SARIMA model is generated by including additional seasonal parameters in ARIMA. The seasonal part of the model consists of parameters that include reverse shifts of the seasonal period.

SARIMA model can be represented as:

$$\varphi_p(L^m)\varphi(L)\nabla_m^D \nabla^d y_t = \theta_Q(L^m)\theta(L)\varepsilon_t, \qquad (4)$$

where the autoregression and moving average parameters are represented by polynomials $\varphi(L)$ and $\theta(L)$ of orders p and q, and the seasonal autoregressive and moving average parameters $\varphi_p(L^m)$ and $\theta_Q(L^m)$ are of orders P and Q. ∇_m^D and ∇^d are the parameters of differentiation of regular and seasonal data; L is the lag operator; m is seasonality.

$$\varphi_p(L^m) = 1 - \varphi_1 L^m - \varphi_2 L^{2m} - \ldots - \varphi_p L^{pm}, \qquad (5)$$

$$\varphi(L) = 1 - \varphi_1(L) - \varphi_2 L^2 - \ldots - \varphi_p L^p, \qquad (6)$$

$$\theta_Q(L^m) = 1 + \theta_1(L^m) + \theta_2(L^{2m}) + \ldots + \theta_Q(L^{Qm}), \qquad (7)$$

$$\nabla_m^D = (1 - L^m)^D, \qquad (8)$$

$$\nabla^d = (1 - L)^d, \qquad (9)$$

$$L^k y_t = y_{t-k}. \qquad (10)$$

Thus, in addition to the three parameters of the ARIMA model: p (trend autoregressive order), d (trend change order), and q (moving average trend), there are four seasonal elements in the SARIMA model: P (seasonal autoregressive order), D (order of seasonal differences), Q (seasonal moving average order) and m (number of time steps in one seasonal period).

2.5. Methods of Data Preprocessing and Preparation

Methods of formal verification and means of software implementation of their main stages have been developed, including the following main parts: compilation semantic-numerical verification, decompilation semantic-numerical verification, and verification of satisfaction of requirements/constraints.

Compilation semantic-numerical verification provides a check of the syntactic and temporal correctness of the formal synthesis of the structures of the semantic-digital specification of verification objects in the dynamics of the design of these objects.

Decompilation semantic-numerical verification verifies the logical equivalence of synthesized multi-parallel programs and/or digital hardware and source codes of C-program tasks after all stages of synthesis are completed (by decompilation of the synthesis result and comparison with the source text). Semantic verification consists in checking (in dynamics or after the completion of all stages of synthesis) the coincidence of units of measurement of physical quantities obtained in the formal synthesis of multi-parallel programs and/or digital hardware, as well as units of measurement of input and input data

of tasks set by users.

Verification of the fulfillment of requirements/restrictions consists in checking the degree of compliance of the requirements/restrictions and is provided by a synthesized software and/or hardware verification object and requirements/restrictions that were specified by the user. The initial data for all types of verification and the basis for maintaining the automatic nature of verification is that at all stages of synthesis, structures of the semantic-numerical specification are formed (including C-programs of tasks; temporal parallel task models; time-parameterized parallel programs; functional, logical and gate circuits parallel hardware, communication topologies of computer networks, etc.). Methods of semantic-numerical formal verification and means of software implementation of the main stages have been developed, which provide an explicit reflection in the designs of parallel programs and digital devices of the units of measurement (semantics) of the processed data, which has a significant impact on the efficiency of software and hardware of parallel computing systems.

Specific examples of formal verification of clock-parameterized semantic-numerical specifications of C-programs of tasks, multi-parallel process models, time-parameterized multi-parallel programs, and digital devices, and software implementations of the main stages

confirm the operability and efficiency of the methods developed and implementing these methods. It should be noted that the authors did not find similar results in the available scientific and technical literature.

3. Results

3.1. Data Preparation

For the study, data on influenza morbidity in the Kharkiv region (Ukraine) for 2017-18, 2018-19, 2019-20, and 2020-21 epidemic seasons were used. Data was provided by the Kharkiv Regional Center for Disease Control and Prevention of the Ministry of Health of Ukraine.

The view of the initial data frame after data import is shown in Figure 1.

After preprocessing and data preparation, it is presented in a form that is convenient for understanding and building a model (Fig. 2).

The next step involves a visual analysis of the data concerning epidemic thresholds (Fig. 3) and an analysis of the distribution of the incidence rate by age group and the general population (Fig. 4).
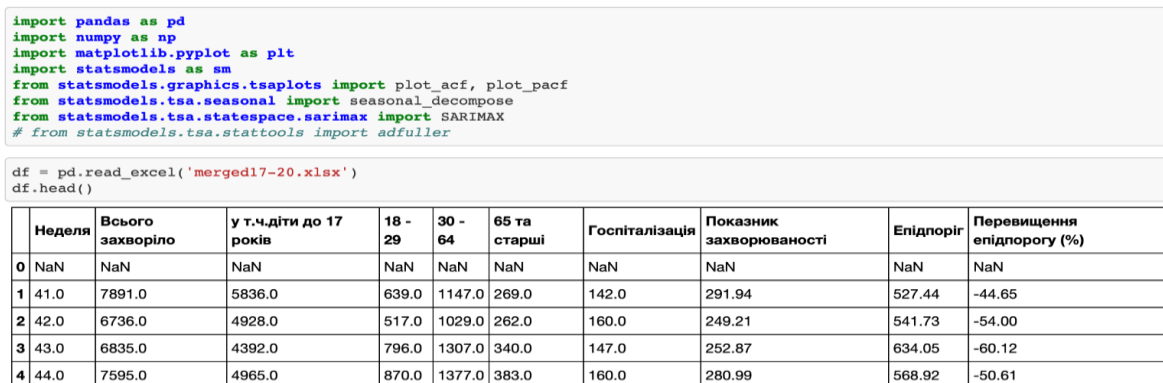
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels as sm
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.statespace.sarimax import SARIMAX
# from statsmodels.tsa.stattools import adfuller
```

```python
df = pd.read_excel('merged17-20.xlsx')
df.head()
```

	Неделя	Всього захворіло	у т.ч.діти до 17 років	18 - 29	30 - 64	65 та старші	Госпіталізація	Показник захворюваності	Епідпорі	Перевищення епідпорогу (%)
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	41.0	7891.0	5836.0	639.0	1147.0	269.0	142.0	291.94	527.44	-44.65
2	42.0	6736.0	4928.0	517.0	1029.0	262.0	160.0	249.21	541.73	-54.00
3	43.0	6835.0	4392.0	796.0	1307.0	340.0	147.0	252.87	634.05	-60.12
4	44.0	7595.0	4965.0	870.0	1377.0	383.0	160.0	280.99	568.92	-50.61

Fig. 1. Initial dataframe

```python
df = df.iloc[1:]
dic = list(df.columns)
col_dict = dict(zip(dic, ['week', 'total','upto17', '18-29', '30-64', '65+', 'hospital', 'indicator', 'epid', 'epid excess']))
df2 = df.rename(columns = col_dict, inplace = False)
df2[['week', 'total', 'upto17', '18-29', '30-64', '65+', 'hospital']] \
= df2[['week', 'total', 'upto17', '18-29', '30-64', '65+', 'hospital']].astype(int)
# df2.set_index('week', inplace=True, drop=True)
df2.head()
```

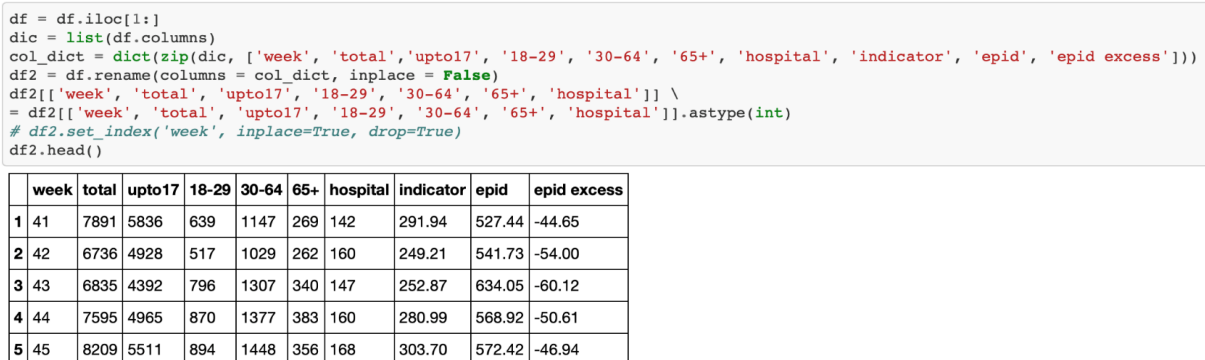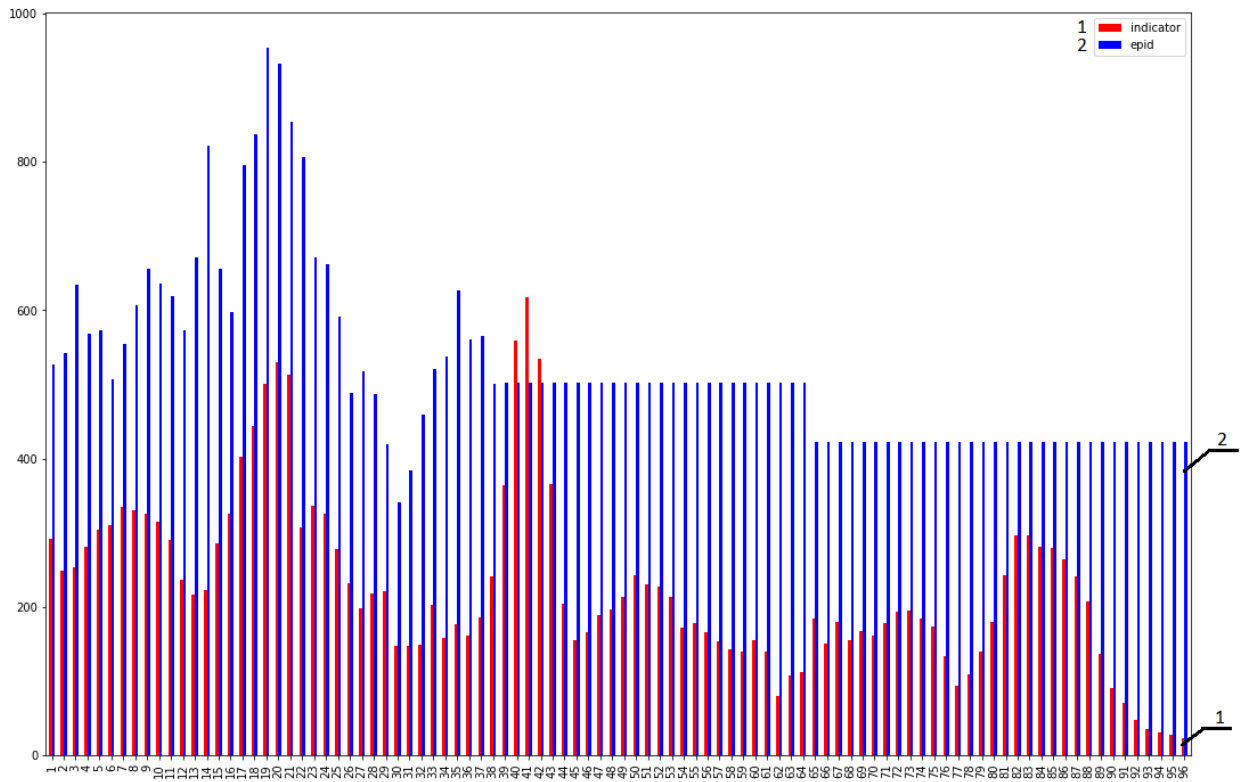|	week	total	upto17	18-29	30-64	65+	hospital	indicator	epid	epid excess
1	41	7891	5836	639	1147	269	142	291.94	527.44	-44.65
2	42	6736	4928	517	1029	262	160	249.21	541.73	-54.00
3	43	6835	4392	796	1307	340	147	252.87	634.05	-60.12
4	44	7595	4965	870	1377	383	160	280.99	568.92	-50.61
5	45	8209	5511	894	1448	356	168	303.70	572.42	-46.94

Fig. 2. Modified dataframe

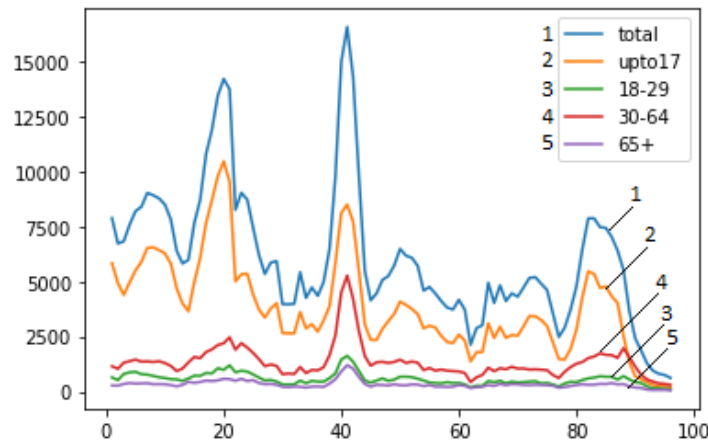Fig. 3. Incidence rate with epidemic thresholds

Fig. 4. distribution of the incidence rate by age group and the general population

3.2. Data Preprocessing

To view the seasonality of the data, we have used a seasonal decomposition to better see the trend of the sample (Fig. 5).

Plots before decomposition into seasonal, trend, seasonality, and residuals are shown in Figures 6-9.

```
decomposition = seasonal_decompose(df2.total, period=7)
fig = plt.figure()
fig = decomposition.plot()
fig.set_size_inches(10, 20)
```

Fig. 5. Seasonal decomposition
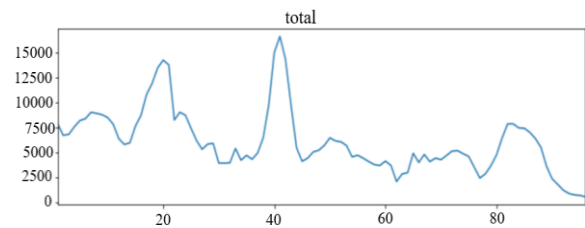
Fig. 6. Data before the decomposition into seasonality
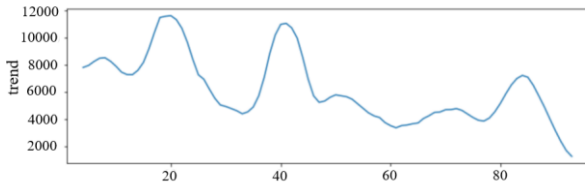
Fig. 7. Trend plot
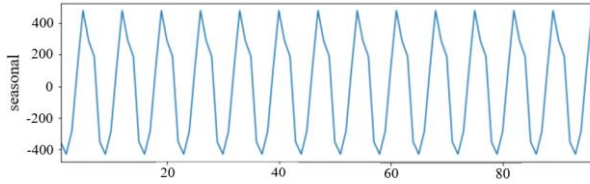
Fig. 8. Seasonality plot
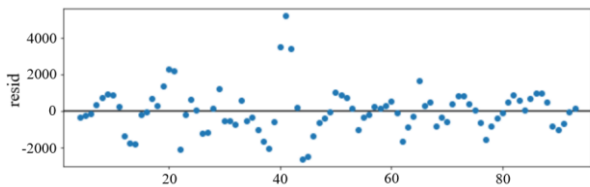
Fig. 9. Residuals plot

3.3. Data Stationing

When using linear regression, it is assumed that all cases are independent of each other. However, in time series, we know that observations are time-dependent. It turns out that many good results that are the result of independent random variables (the law of large numbers and the central limit theorem, for example) adhere to stationary random variables. Thus, by making the data stationary, we can apply regression methods to this time-dependent variable.

The easiest way to check data for stationarity is visual. But for a more accurate assessment, there is the Dickey-Fuller test [35]. If the test statistic is greater than the Critical Value, then the time series are stationary. The result of checking the data for stationarity is shown in Figure 10.

Our task is to make the Test Statistic parameter less than the Critical Value (1 %). Even though we have already achieved this, it is better to achieve a larger finite difference, so we will also find the first difference for our data.

The first time series difference is a series of changes from one period to the next. If Y_t denotes the value of time series Y over period t, then the first difference Y over period t is equal to $Y_t - Y_{t-1}$. If the first difference Y is stationary and also completely random (not autocorrelated), then Y is described by a random walk model: each value is a random step from the previous value. If the first difference Y is stationary but not completely random –

that is, if its value in period t is automatically correlated with its value in previous periods - then a more complex forecasting model such as exponential smoothing or ARIMA, as in our case, may be appropriate (Fig. 11).
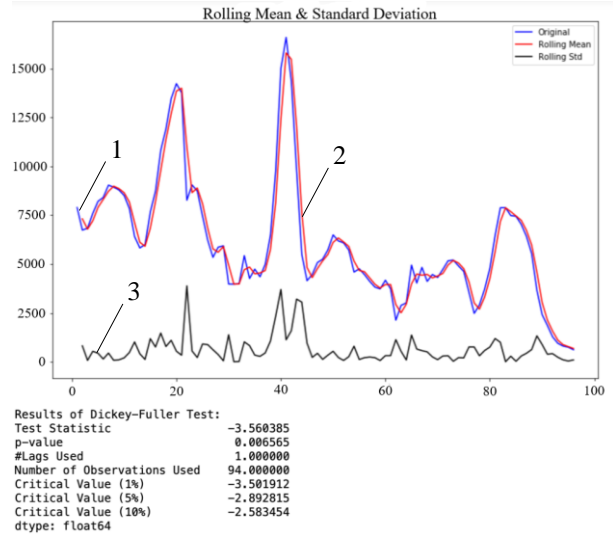

Fig. 10. Results of Dickey-Fuller Test:
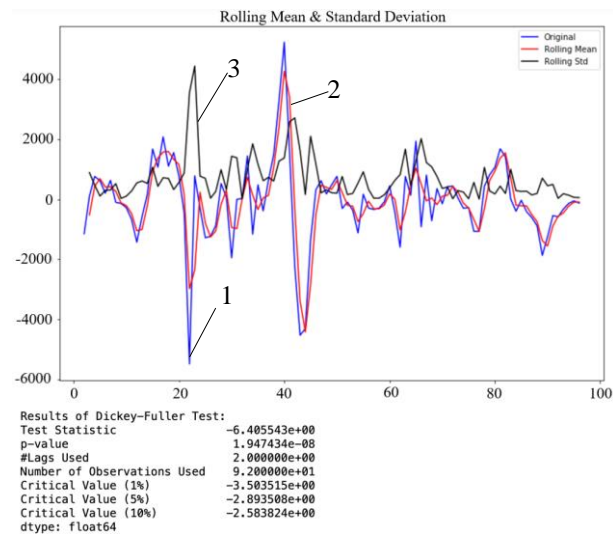1 – Original, 2 – Rolling Mean, 3 – Rolling Std

Fig. 11. Data stationarity plot for the first difference:
1 – Original, 2 – Rolling Mean, 3 – Rolling Std

The next step is to find the optimal model parameters using the computational capabilities of the Python language. All parameters of the constructed model are shown in Figure 12.

3.4. Forecasting

On the basis of statistics on the incidence of influenza in the Kharkiv region, a short-term forecast of the dynamics of the incidence for 10 weeks was built (Fig. 13). Such a forecast can be used by persons making

```
==============================================================================
Dep. Variable:                           total   No. Observations:            96
Model:            SARIMAX(2, 1, 2)x(2, 1, 2, 32)   Log Likelihood         -521.940
Date:                         Sat, 03 Jul 2021   AIC                      1061.879
Time:                                 17:32:10   BIC                      1081.167
Sample:                                      0   HQIC                     1069.465
                                         - 96
Covariance Type:                           opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.1559      0.303      3.816      0.000       0.562       1.750
ar.L2         -0.4266      0.264     -1.613      0.107      -0.945       0.092
ma.L1         -0.9006      0.401     -2.247      0.025      -1.686      -0.115
ma.L2         -0.0872      0.393     -0.222      0.824      -0.858       0.684
ar.S.L32      -0.7589      3.700     -0.205      0.837      -8.010       6.493
ar.S.L64      -0.7793      0.436     -1.787      0.074      -1.634       0.075
ma.S.L32      -1.7092     17.578     -0.097      0.923     -36.161      32.742
ma.S.L64       0.9264     47.716      0.019      0.985     -92.596      94.449
sigma2       6.853e+04      0.000   1.78e+08      0.000    6.85e+04    6.85e+04
==============================================================================
Ljung-Box (L1) (Q):                   2.82   Jarque-Bera (JB):           27.86
Prob(Q):                              0.09   Prob(JB):                    0.00
Heteroskedasticity (H):               0.47   Skew:                        0.99
Prob(H) (two-sided):                  0.09   Kurtosis:                    5.59
==============================================================================
```
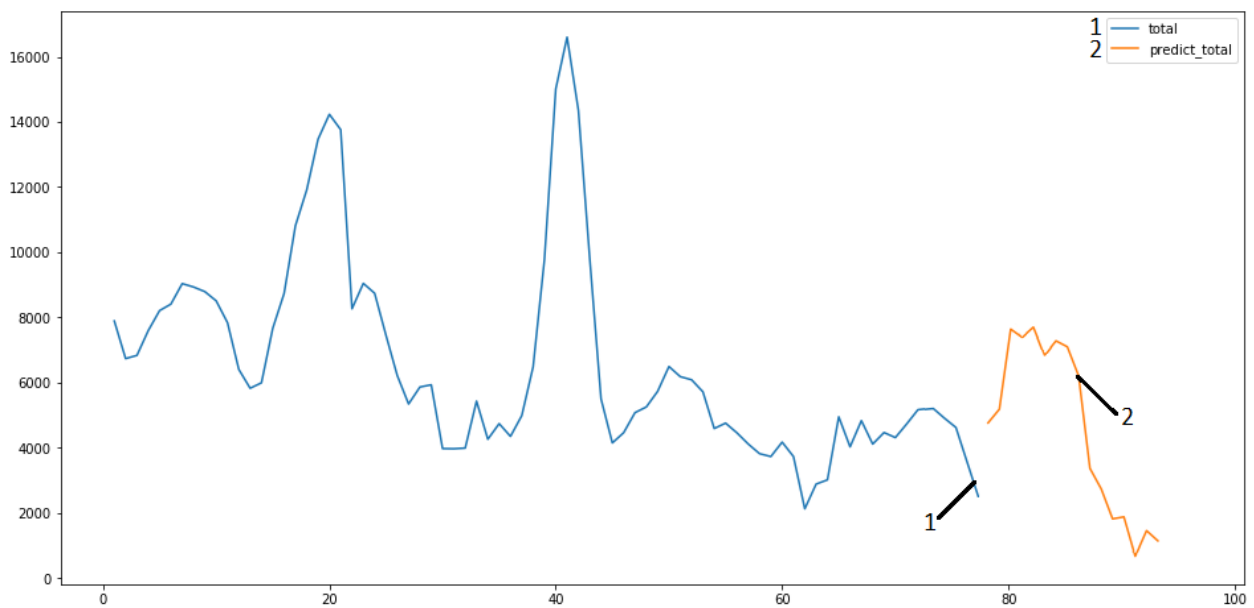
Fig. 12. Parameters of the model

Fig. 13. Forecast of influenza epidemic process

decisions on the implementation of anti-epidemic and deterrent measures in the event that the forecast exceeds the epidemic thresholds of morbidity.

Conclusions

The paper describes experimental research on the implementation of the SARIMA model to the epidemic process of influenza simulation. Models were verified by influenza morbidity in the Kharkiv region (Ukraine) for the 2017-18, 2018-19, 2019-20, and 2020-21 epidemic seasons. Data was provided by the Kharkiv Regional Center for Disease Control and Prevention of the Ministry of Health of Ukraine.

The novelty of the research is the development of an epidemic process model based on state-of-art methods and approaches applied to the influenza epidemic process in a certain territory. The distinctive point about the proposed study is that the model includes the seasonality of the influenza epidemic process. It allows increasing the accuracy of the developed forecast.

The obtained forecasting result has sufficient accuracy for planning prophylactic and control measures for the next epidemic season of influenza and influenza-like diseases in Ukraine. These activities include planning the provision of hospitals and health facilities with influenza drugs, planning the provision of beds and redesigning hospitals, and strengthening the information campaign on the need for annual influenza vaccination. In the context of the current COVID-19 pandemic, it is extremely important to plan material resources that can be reallocated from the influenza campaign to activities related to the provision and support of patients with the new version of coronavirus.

The forecasting results show a downward trend in the dynamics of the epidemic process of influenza in the Kharkiv region. This is due to the introduction of anti-epidemic measures aimed at combating COVID-19. Activities such as wearing masks, social distancing, and lockdowns also contribute to reducing seasonal influenza epidemics. The main carriers of the influenza virus are children and young people who have the most active life-style, characterized by a high chance to contact. Therefore, distance learning in schools, and higher education institutions, the closure of public places, restrictions on public transport, and the prohibition of mass events are affecting the reduction of the spread of the virus. The decrease in the diagnosis of influenza due to the high incidence of COVID-19 also has an impact on reducing the incidence of influenza and influenza-like infections in Ukraine. According to the low level of annual vaccination against influenza in Ukraine, it is not a decisive factor in reducing the intensification of the epidemic process. Nevertheless, vaccination is an effective tool to reduce the dynamics of the incidence of influenza and influenza-like infections in Ukraine.

Future research development. The constructed model showed sufficient forecast accuracy for adjusting anti-epidemic measures planned to reduce the incidence of influenza and influenza-like infections in Ukraine. However, statistical methods prohibit identifying factors influencing the dynamics of the epidemic process. Thus, it is planned to build an intelligent multiagent model that takes into account the peculiarities of the behavior of the population and the circulation of the virus in it. The multiagent model will make it possible to conduct an experimental study of the informativeness and significance of the model parameters, which will make it possible to evaluate the effectiveness of specific measures aimed at reducing the epidemic incidence. At the same time, to improve the accuracy of the multiagent model, it is supposed to be calibrated on the SARIMA model proposed in this paper, which will improve the accuracy of the obtained forecast
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References (GOST 7.1:2006)

1. Paget, J. Preventing seasonal influenza worldwide through vaccination, education, and international cooperation: research, findings, and recommendations from the Global Influenza Initiative [Text] / J. Paget // Influenza and Other Respiratory Viruses. – 2015. – vol. 9, suppl. 1. – P. 1-2. DOI: 10.1111/irv.12327.

2. Hay, A. J. The WHO global influenza surveillance and response system (GISRS)-A future perspective [Text] / A.J. Hay, J.W. McCauley // Influenza and Other Respiratory Viruses. – 2018. – vol. 12, iss. 5. – P. 551-557. DOI: 10.1111/irv.12565.

3. Bresee, J. Epidemic influenza--responding to the expected but unpredictable [Text] / J. Bresee, F.G. Hayden // The New England Journal of Medicine. – 2013. – vol. 368, iss. 7. – P. 589-92. DOI: 10.1056/NEJMp1300375.

4. Solomon, D. A. Influenza in the COVID-19 Era [Text] / D. A. Solomon, A. C. Sherman, S. Kanjilal // Journal of American Medical Association. – 2020. – vol. 324, iss. 13. – P. 1342-1343. DOI: 10.1001/jama.2020.14661.

5. Expanding the pandemic influenza preparedness framework to the epidemic of COVID-19 [Text] / B. Z. Li, M. S. Li, J. Y. Huang, Y. Y. Chen, Y. H. Lu // Zhonghua Yu Fang Yi Xue Za Zhi. – 2020. – vol. 54, iss. 6. – P. 597-601. DOI: 10.3760/cma.j.cn112150-20200316-00357.

6. Wormser, G. P. COVID-19 versus seasonal influenza 2019-2020: USA [Text] / G. P. Wormser // Wiener Klinische Wochenschrift. – 2020. – vol. 132, iss. 13-14. – P. 387-389. DOI: 10.1007/s00508-020-01685-y.

7. A Case Series of Patients Coinfected With Influenza and COVID-19 [Text] / V. M. Konala, et. al. // Journal of Investigative Medicine High Impact Case Reports. – 2020. – vol. 8. DOI: 10.1177/2324709620934674.

8. Nutritional practices as an obesogenic predictor in school-age children from eastern and western regions of Ukraine [Text] / T. Chaychenko, et. al. // Problemi Endokrinnoi Patologii. – 2021. – vol. 1. – P. 75-83. DOI: 10.21856/j-PEP.2021.1.10.

9. Bagcchi, S. Ukraine struggles to implement flu vaccination [Text] / S. Bagcchi // The Lancet. Respiratory Medicine. – 2016. – vol. 4, iss. 7. – P. 541-542. DOI: 10.1016/S2213-2600(16)30141-2.

10. Very little influenza in the WHO European Region during the 2020/21 season, weeks 40 2020 to 8 2021 [Text] / C. Adlhoch, P. Mook, F. Lamb, L. Ferland, A. Melidou, A. J. Amato-Gauci, R. Pebody // Euro Surveillance. – 2021. – vol. 26, iss. 11, pii: 2100221. DOI: 10.2807/1560-7917.ES.2021.26.11.2100221.

11. The concept of developing a decision support system for the epidemic morbidity control [Text] / S. Yakovlev, K. Bazilevych, D. Chumachenko, T. Chumachenko, L. Hulianytskyi, I. Meniailov, A. Tkachenko // CEUR Workshop Proceedings. – 2020. – vol. 2753. – P. 265–274.

12. Rvachev, L. A. A mathematical model for the global spread of influenza [Text] / L. A. Rvachev, I. M. Longini Jr. // Mathematical Biosciences. – 1985. – vol. 75, iss. 1. – P. 3-22. DOI: 10.1016/0025-5564(85)90064-1.

13. Comparing three basic models for seasonal influenza [Text] / S. Edlund, et. al. // Epidemics. – 2011. – vol. 3, iss. 3-4. – P. 135-142. DOI: 10.1016/j.epidem.2011.04.002.

14. Levy, N. Modeling influenza-like illnesses through composite compartmental models [Text] / N. Levy, M. Lv, E. Yom-Tov // Physica A: Statistical Mechanical and its Applications. – 2018. – vol. 494. – P. 288-293. DOI: 10.1016/j.physa.2017.12.052.

15. Fudolig, M. The local stability of a modified multi-strain SIR model for emerging viral strains [Text] / M. Fudolig, R. Howard // PLoS ONE. – 2020. – vol. 15, iss. 12. DOI: 10.1371/journal.pone.0243408.

16. Kanyiri, C.W. Mathematical Analysis of Influenza A Dynamics in the Emergence of Drug Resistance [Text] / C.W. Kanyiri, M. Kimathi, L. Livingstone // Computational and Mathematical Methods in Medicine. – 2018. – vol. 2018. DOI: 10.1155/2018/2434560.

17. Roosa, K. Assessing parameter identifiability in compartmental dynamic models using a computational approach: application to infectious disease transmission models [Text] / K. Roosa, G. Chowell // Theoretical Biology and Medical Modelling. – 2019. – vol. 16, iss. 1. DOI: 10.1186/s12976-018-0097-6.

18. Caini, S. Important changes in the timing of influenza epidemics in the WHO European Region over the past 20 years: virological surveillance 1996 to 2016 [Text] / S. Caini, F. Schellevis, S.C. El-Guerche, J. Paget // Euro Surveillance. – 2018. – vol. 23, iss. 1. DOI: 10.2807/1560-7917.ES.2018.23.1.17-00302.

19. Steiner, S. H. Detecting the start of an influenza outbreak using exponentially weighted moving average charts [Text] / S. H. Steiner, K. Grant, M. Coory, H. A. Kelly // BMC Medical Informatics and Decision Making. – 2010. – vol. 10, 37. DOI: 10.1186/1472-6947-10-37.

20. Solgi, M. Timely detection of influenza outbreaks in Iran: evaluation the performance of the exponentially weighted moving average [Text] / M. Solgi, M. Karami, J. Poorolajal // Journal of Infection and Public Health. – 2018. – vol. 11, iss. 3. – P. 389-392. DOI: 10.1016/j.jiph.2017.09.011.

21. Choi, S. B. Forecasting type-specific seasonal influenza after 26 weeks in the United States using influenza activities in other countries [Text] / S. B. Choi, J. Kim, I. Ahn // PLoS ONE. – 2019. – vol. 14, iss. 11. DOI: 10.1371/journal.pone.0220423.

22. He, Z. Epidemiology and ARIMA model of positive-rate of influenza viruses among children in Wuhan, China: a nine-year retrospective study [Text] / Z. He, H. Tao // International Journal of Infectious Diseases. – 2018. – vol. 74. – P. 61-70. DOI: 10.1016/j.ijid.2018.07.003.

23. Zhu, G. Forecasting influenza based on autoregressive moving average and holt-winters exponential smoothing models [Text] / G. Zhu, L. Li, Y. Zheng, X. Zhang, H. Zou // Journal of Advanced Computational Intelligence and Intelligent Informatics. – 2021. – vol. 25, iss. 1. – P. 138-144. DOI: 10.20965/JACIII.2021.P0138.

24. Kushnir, M. Artificial intelligence systems in the financial market predictions: literature review [Text] / M. Kushnir, K. Tokareva // Radioelectronic and Computer Systems. – 2020. – No. 3(95). – P. 108-117. DOI: 10.32620/reks.2020.3.11.

25. Predictive modeling based on small data in clinical medicine: RBF-based additive input-doubling method [Text] / I. Izonin, R. Tkachenko, I. Dronyuk, P. Tkachenko, M. Gregus, M. Rashkevych // Mathematical Biosciences and Engineering. – 2021. – vol. 18, iss. 3. – P. 2599-2613. DOI: 10.3934/mbe.2021132.

26. Method of Data Openness Estimation Based on User-Experience in Infocommunication Systems of Municipal Enterprises [Text] / V. Yesina, N. Matveeva, I. Chumachenko, N. Manakova // 2018 International Scientific-Practical Conference on Problems of Infocommunications Science and Technology, PIC S and T 2018 – Proceedings. – 2019. – P. 171–176. DOI: 10.1109/INFOCOMMST.2018.8631897.

27. Fedorov, E. Approaches to the creation of a software agent based on meta-heuristic and artificial neural networks [Text] / E. Fedorov, M. Chychuzhko, V. Chychuzhko // Radioelectronic and Computer Systems. – 2019. – No. 1(89). – P. 58-65. DOI: 10.32620/reks.2019.1.06.

28. Fedushko, S. Operational Intelligence Software Concepts for Continuous Healthcare Monitoring and Consolidated Data Storage Ecosystem [Text] / S. Fedushko, T. Ustyianovych // Advances in Intelligent Systems and Computing. – 2021. – Vol. 1247. – P. 545–557. DOI: 10.1007/978-3-030-55506-1_49.

29. Assessment of measurement uncertainty of the uncinated process and middle nasal concha in spiral computed tomography data [Text] / A. Nechyporenko, V. Reshetnik, V. Alekseeva, N. Yurevych, R. Nazaryan, V. Gargin // 2019 IEEE International Scientific-Practical Conference: Problems of Infocommunications Science and Technology, PIC S and T 2019 – Proceedings. – 2019. – P. 585-588. DOI: 10.1109/PICST47496.2019.9061557.

30. Dotsenko, S. Intellectual systems: principles of the heuristic self-organization of the processes of sense thinking and sense activity [Text] / S. Dotsenko // Radioelectronic and Computer Systems. – 2020. – No. 2(94). – P. 4-21. DOI: 10.32620/reks.2020.2.01.

31. Prediction of filtering efficiency for DCT-based image denoising [Text] / S. Abramov, S. Krivenko, A. Roenko, V. Lukin, I. Djurovic, M. Chobanu // Pro-

ceedings – 2013, 2nd Mediterranean Conference on Embedded Computing, MECO 2013. – 2013. – P. 97. DOI: 10.1109/MECO.2013.6601327.

32. Tea Quality Prediction by Autoregressive Modeling of Electronic Tongue Signals [Text] / P. Saha, S. Ghorai, B. Tudu, R. Bandyopadhyay, N. Bhattacharyya // IEEE Sensors Journal. – 2016. – vol. 16, no. 11. – P. 4470-4477. DOI: 10.1109/JSEN.2016.2544979.

33. Wang, Y. Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost [Text] / Y. Wang, Y. Guo // China Communications. – 2020. – vol. 17, no. 3. – P. 205-221. DOI: 10.23919/JCC.2020.03.017.

34. Ogino, Y. Forecasting Bowel Sound Occurrence Frequency by SARIMA Model [Text] / Y. Ogino, Y. Satoh, O. Sakata // 2019 23rd International Computer Science and Engineering Conference (ICSEC). – 2019. – P. 219-223, DOI: 10.1109/ICSEC47112.2019.8974803.

35. Tayeb, H. F. Time Series Database Preprocessing for Data Mining Using Python [Text] / H. F. Tayeb, M. Karabatak, C. Varol // 2020 8th International Symposium on Digital Forensics and Security (ISDFS). – 2020. – P. 1-4, DOI: 10.1109/ISDFS49300.2020.9116260.

References (BSI)

1. Paget J. Preventing seasonal influenza worldwide through vaccination, education, and international cooperation: research, findings, and recommendations from the Global Influenza Initiative. *Influenza and Other Respiratory Viruses*, 2015, vol. 9, suppl. 1, pp. 1-2. DOI: 10.1111/irv.12327.

2. Hay, A. J., McCauley, J. W. The WHO global influenza surveillance and response system (GISRS)-A future perspective. *Influenza and Other Respiratory Viruses*, 2018, vol. 12, iss. 5, pp. 551-557. DOI: 10.1111/irv.12565.

3. Bresee, J., Hayden, F.G. Epidemic influenza--responding to the expected but unpredictable. *The New England Journal of Medicine*, 2013, vol. 368, iss. 7, pp. 589-92. DOI: 10.1056/NEJMp1300375.

4. Solomon, D. A., Sherman, A. C., Kanjilal, S. Influenza in the COVID-19 Era. *Journal of American Medical Association*, 2020, vol. 324, iss. 13, pp. 1342-1343. DOI: 10.1001/jama.2020.14661.

5. Li, B. Z., Li, M. S., Huang, J. Y., Chen, Y. Y., Lu, Y. H. Expanding the pandemic influenza preparedness framework to the epidemic of COVID-19. *Zhonghua Yu Fang Yi Xue Za Zhi*, 2020, vol. 54, iss. 6, pp. 597-601. DOI: 10.3760/cma.j.cn112150-20200316-00357.

6. Wormser, G. P. COVID-19 versus seasonal influenza 2019-2020: USA. *Wiener Klinische Wochenschrift*, 2020, vol. 132, iss. 13-14, pp. 387-389. DOI: 10.1007/s00508-020-01685-y.

7. Konala, V. M., et. al. A Case Series of Patients Coinfected With Influenza and COVID-19. *Journal of Investigative Medicine High Impact Case Reports*, 2020, vol. 8. DOI: 10.1177/2324709620934674.

8. Chaychenko, T., et. al. Nutritional practices as an obesogenic predictor in school-age children from eastern and western regions of Ukraine. *Problemi Endokrinnoi Patologii,* 2021, vol. 1, pp. 75-83. DOI: 10.21856/j-PEP.2021.1.10.

9. Bagcchi, S. Ukraine struggles to implement flu vaccination. *The Lancet. Respiratory Medicine*, 2016, vol. 4, iss. 7, pp. 541-542. DOI: 10.1016/S2213-2600(16)30141-2.

10. Adlhoch, C., Mook, P., Lamb, F., Ferland, L., Melidou, A., Amato-Gauci, A. J., Pebody, R. Very little influenza in the WHO European Region during the 2020/21 season, weeks 40 2020 to 8 2021. *Euro Surveillance*, 2021, vol. 26, iss. 11, pii: 2100221. DOI: 10.2807/1560-7917.ES.2021.26.11.2100221.

11. Yakovlev, S., Bazilevych, K., Chumachenko, D., Chumachenko, T., Hulianytskyi, L., Meniailov, I., Tkachenko, A. The concept of developing a decision support system for the epidemic morbidity control. *CEUR Workshop Proceedings*, 2020, vol. 2753, pp. 265–274.

12. Rvachev, L. A., Longini Jr., I. M. A mathematical model for the global spread of influenza. *Mathematical Biosciences,* 1985, vol. 75, iss. 1, pp. 3-22. DOI: 10.1016/0025-5564(85)90064-1.

13. Edlund, S., et. al. Comparing three basic models for seasonal influenza. *Epidemics,* 2011, vol. 3, iss. 3-4, pp. 135-142. DOI: 10.1016/j.epidem.2011.04.002.

14. Levy, N., Lv, M., Yom-Tov, E. Modeling influenza-like illnesses through composite compartmental models. *Physica A: Statistical Mechanical and its Applications,* 2018, vol. 494, pp. 288-293. DOI: 10.1016/j.physa.2017.12.052.

15. Fudolig, M., Howard, R. The local stability of a modified multi-strain SIR model for emerging viral strains. *PLoS ONE*, 2020, vol. 15, iss. 12. DOI: 10.1371/journal.pone.0243408.

16. Kanyiri, C.W., Kimathi, M., Livingstone, L. Mathematical Analysis of Influenza A Dynamics in the Emergence of Drug Resistance. *Computational and Mathematical Methods in Medicine,* 2018, vol. 2018. DOI: 10.1155/2018/2434560.

17. Roosa, K., Chowell, G. Assessing parameter identifiability in compartmental dynamic models using a computational approach: application to infectious disease transmission models. *Theoretical Biology and Medical Modelling,* 2019, vol. 16, iss. 1. DOI: 10.1186/s12976-018-0097-6.

18. Caini, S., Schellevis, F., El-Guerche, S.C., Paget, J. Important changes in the timing of influenza epidemics in the WHO European Region over the past 20 years: virological surveillance 1996 to 2016. *Euro Surveillance*, 2018, vol. 23, iss. 1. DOI: 10.2807/1560-7917.ES.2018.23.1.17-00302.

19. Steiner, S. H., Grant, K., Coory, M., Kelly, H. A. Detecting the start of an influenza outbreak using exponentially weighted moving average charts. *BMC Medical Informatics and Decision Making,* 2010, vol. 10, 37. DOI: 10.1186/1472-6947-10-37.

20. Solgi, M., Karami, M., Poorolajal, J. Timely detection of influenza outbreaks in Iran: evaluation the performance of the exponentially weighted moving average. *Journal of Infection and Public Health,* 2018, vol. 11, iss. 3, pp. 389-392. DOI: 10.1016/j.jiph.2017.09.011.

21. Choi, S. B., Kim, J., Ahn, I. Forecasting type-specific seasonal influenza after 26 weeks in the United States using influenza activities in other countries. *PLoS ONE*, 2019, vol. 14, iss. 11, DOI: 10.1371/journal.pone.0220423.

22. He, Z., Tao, H. Epidemiology and ARIMA model of positive-rate of influenza viruses among children in Wuhan, China: a nine-year retrospective study. *International Journal of Infectious Diseases,* 2018, vol. 74, pp. 61-70. DOI: 10.1016/j.ijid.2018.07.003.

23. Zhu, G., Li, L., Zheng, Y., Zhang, X., Zou, H. Forecasting influenza based on autoregressive moving average and holt-winters exponential smoothing models. *Journal of Advanced Computational Intelligence and Intelligent Informatics,* 2021, vol. 25, iss. 1, pp. 138-144. DOI: 10.20965/JACIII.2021.P0138.

24. Kushnir, M., Tokareva, K. Artificial intelligence systems in the financial market predictions: literature review. *Radioelectronic and Computer Systems,* 2020, no. 3(95), pp. 108-117. DOI: 10.32620/reks.2020.3.11.

25. Izonin, I., Tkachenko, R., Dronyuk, I., Tkachenko, P., Gregus, M., Rashkevych, M. Predictive modeling based on small data in clinical medicine: RBF-based additive input-doubling method. *Mathematical Biosciences and Engineering*, 2021, vol. 18, iss. 3, pp. 2599-2613. DOI: 10.3934/mbe.2021132.

26. Yesina, V., Matveeva, N., Chumachenko, I., Manakova, N. Method of Data Openness Estimation Based on User-Experience in Infocommunication Systems of Municipal Enterprises. *2018 International Scientific-Practical Conference on Problems of Infocommunications Science and Technology, PIC S and T 2018 – Proceedings*, 2019, pp. 171–176. DOI: 10.1109/INFOCOMMST.2018.8631897.

27. Fedorov, E., Chychuzhko, M., Chychuzhko, V. Approaches to the creation of a software agent based on meta-heuristic and artificial neural networks. *Radioelectronic and Computer Systems,* 2019, no. 1(89), pp. 58-65. DOI: 10.32620/reks.2019.1.06.

28. Fedushko, S., Ustiyanovych, T. Operational Intelligence Software Concepts for Continuous Healthcare Monitoring and Consolidated Data Storage Ecosystem. *Advances in Intelligent Systems and Computing*, 2021, vol. 1247, pp. 545–557. DOI: 10.1007/978-3-030-55506-1_49.

29. Nechyporenko, A., Reshetnik, V., Alekseeva, V., Yurevych, N., Nazaryan, R., Gargin, V. Assessment of measurement uncertainty of the uncinated process and middle nasal concha in spiral computed tomography data. *2019 IEEE International Scientific-Practical Conference: Problems of Infocommunications Science and Technology, PIC S and T 2019 - Proceedings,* 2019, pp. 585-588. DOI: 10.1109/PICST47496.2019.9061557.

30. Dotsenko, S. Intellectual systems: principles of the heuristic self-organization of the processes of sense thinking and sense activity. *Radioelectronic and Computer Systems,* 2020, no. 2(94), pp. 4-21. DOI: 10.32620/reks.2020.2.01.

31. Abramov, S., Krivenko, S., Roenko, A., Lukin, V., Djurovic, I., Chobanu, M. Prediction of filtering efficiency for DCT-based image denoising, *Proceedings – 2013, 2nd Mediterranean Conference on Embedded Computing, MECO 2013*, 2013, pp. 97. DOI: 10.1109/MECO.2013.6601327.

32. Saha, P., Ghorai, S., Tudu, B., Bandyopadhyay, R., Bhattacharyya, N. Tea Quality Prediction by Autoregressive Modeling of Electronic Tongue Signals. *IEEE Sensors Journal*, 2016, vol. 16, no. 11, pp. 4470-4477. DOI: 10.1109/JSEN.2016.2544979.

33. Wang, Y., Guo, Y. Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost, *China Communications*, 2020, vol. 17, no. 3, pp. 205-221. DOI: 10.23919/JCC.2020.03.017.

34. Ogino, Y., Satoh, Y., Sakata, O. Forecasting Bowel Sound Occurrence Frequency by SARIMA Model. *2019 23rd International Computer Science and Engineering Conference (ICSEC)*, 2019, pp. 219-223, DOI: 10.1109/ICSEC47112.2019.8974803.

35. Tayeb, H. F., Karabatak, M., Varol, C. Time Series Database Preprocessing for Data Mining Using Python. *2020 8th International Symposium on Digital Forensics and Security (ISDFS)*, 2020, pp. 1-4, DOI: 10.1109/ISDFS49300.2020.9116260.

МОДЕЛЮВАННЯ І ПРОГНОЗУВАННЯ ЕПІДЕМІЧНОГО ПРОЦЕСУ ГРИПУ ЗА ДОПОМОГОЮ МОДЕЛІ СЕЗОННОЇ АВТОРЕГРЕСІЙНОЇ ІНТЕГРОВАНОЇ КОВЗНОЇ СЕРЕДНЬОЇ

Д. І. Чумаченко, Є. С. Меняйлов, А. А. Грімов, В. В. Лопатка,
О. Ю. Мороз, О. Г. Толстолузька

Сьогоднішня глобальна пандемія COVID-19 вплинула на поширення грипу. COVID-19 та грип є респіраторними інфекціями та мають ряд схожих симптомів. Але вони викликаються різними вірусами. Є також деякі відмінності в категоріях людей, найбільш схильних до ризику важких форм цих захворювань. Стратегії їхнього лікування також різні. Математичне моделювання – ефективний інструмент контролю епідемічного

процесу грипу на визначених територіях. Результати моделювання та прогнози, отримані за допомогою імітаційних моделей, дозволяють своєчасно розробити обґрунтовані протиепідемічні заходи щодо зниження динаміки захворюваності на грип. **Метою статті** є розробка моделі сезонного авторегресійного інтегрованого ковзного середнього (SARIMA) для моделювання епідемічного процесу грипу та дослідження експериментальних результатів моделювання. **Об'єкт дослідження** – епідемічний процес грипу та його динаміка на території України. **Предметом дослідження** є моделі та методи імітаційного моделювання епідемічних процесів, у тому числі методи машинного навчання, зокрема модель SARIMA. Для досягнення мети дослідження ми використовували **методи** прогнозування та побудували модель SARIMA епідемічного процесу грипу. У **результаті** експериментів з розробленою моделлю було отримано прогнозну динаміку епідемічного процесу грипу на 10 тижнів. Такий прогноз може бути використаний особами, що приймають рішення про реалізацію протиепідемічних і стримуючих заходів у разі перевищення прогнозом епідемічних порогів захворюваності. **Висновки.** У статті описані експериментальні дослідження щодо застосування моделі SARIMA для моделювання епідемічного процесу грипу. Моделі верифіковані на захворюваності на грип у Харківській області (Україна) за епідемічні сезони 2017-18, 2018-19, 2019-20 та 2020-21 рр. Дані надані Харківським обласним центром з контролю та профілактики захворювань Міністерства охорони здоров'я України. Результати прогнозування показують тенденцію до зниження динаміки епідемічного процесу грипу у Харківській області. Це пов'язано з введенням протиепідемічних заходів, вкладених у боротьбу з COVID-19. Такі дії, як носіння масок, соціальне дистанціювання та ізоляція також сприяють зниженню епідемічної захворюваності на сезонний грип.

Ключові слова: модель епідемії; епідемічний процес; моделювання епідемії; імітаційне моделювання; модель SARIMA; грип.

МОДЕЛИРОВАНИЕ И ПРОГНОЗИРОВАНИЕ ЭПИДЕМИЧЕСКОГО ПРОЦЕССА ГРИППА С ПОМОЩЬЮ МОДЕЛИ СЕЗОННОГО АВТОРЕГРЕССИОННОГО ИНТЕГРИРОВАННОГО СКОЛЬЗЯЩЕГО СРЕДНЕГО

Д. И. Чумаченко, Е. С. Меняйлов, А. А. Гримов, В. В. Лопатка,
О. Ю. Мороз, Е. Г. Толстолужская

Сегодняшняя глобальная пандемия COVID-19 повлияла на распространение гриппа. COVID-19 и грипп являются респираторными инфекциями и имеют ряд схожих симптомов. Однако они вызываются различными вирусами. Есть также некоторые различия в категории людей, наиболее подверженных риску тяжелых форм этих заболеваний. Стратегии их лечения также разные. Математическое моделирование – эффективный инструмент контроля эпидемического процесса гриппа на определенных территориях. Результаты моделирования и прогнозы, полученные с помощью имитационных моделей, позволяют своевременно разработать обоснованные противоэпидемические меры по снижению динамики заболеваемости гриппом. **Целью статьи** является разработка модели сезонного авторегрессионного интегрированного скользящего среднего (SARIMA) для моделирования эпидемического процесса гриппа и исследование экспериментальных результатов моделирования. **Объект исследования** – эпидемический процесс гриппа и его динамика на территории Украины. **Предметом исследования** являются модели и методы имитационного моделирования эпидемических процессов, в том числе методы машинного обучения, в частности модель SARIMA. Для достижения цели исследования мы использовали **методы** прогнозирования и построили модель SARIMA эпидемического процесса гриппа. В **результате** экспериментов с разработанной моделью была получена прогнозная динамика эпидемического процесса гриппа на 10 недель. Такой прогноз может быть использован лицами, принимающими решения о реализации противоэпидемических и сдерживающих мер в случае превышения прогнозом эпидемических порогов заболеваемости. **Выводы.** В статье описаны экспериментальные исследования по применению модели SARIMA к моделированию эпидемического процесса гриппа. Модели верифицированы на заболеваемости гриппом в Харьковской области (Украина) за эпидемические сезоны 2017-18, 2018-19, 2019-20 и 2020-21 гг. Данные предоставлены Харьковским областным центром по контролю и профилактике заболеваний Министерства здравоохранения Украины. Результаты прогнозирования показывают тенденцию к снижению динамики эпидемического процесса гриппа в Харьковской области. Это связано с введением противоэпидемических мероприятий, направленных на борьбу с COVID-19. Такие действия, как ношение масок, социальное дистанцирование и изоляция также способствуют снижению эпидемической заболеваемости сезонного гриппа.

Ключевые слова: модель эпидемии; эпидемический процесс; моделирование эпидемии; имитационное моделирование; модель SARIMA; грипп.

Чумаченко Дмитро Ігорович – канд. техн. наук, доц., доц. каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Меняйлов Євген Сергійович – канд. техн. наук, старш. викл. каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Грімов Андрій Артемович – здобувач каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Лопатка Владислав Вадимович – здобувач каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Мороз Ольга Юріївна – ст. викл. каф. теоретичної та прикладної системотехніки, Харківський національний університет імені В.Н. Каразіна, Харків, Україна

Толстолузька Олена Геннадіївна – д-р техн. наук, старш. наук. співроб., проф. каф. теоретичної та прикладної системотехніки, Харківський національний університет імені В. Н. Каразіна, Харків, Україна.

Dmytro Chumachenko – PhD in Artificial Intelligence, Associate Professor of Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine, e-mail: dichumachenko@gmail.com, ORCID: 0000-0003-2623-3294.

Ievgen Meniailov – PhD in Mathematical Modelling and Optimization Methods, Senior Lecturer of Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine,
e-mail: evgenii.menyailov@gmail.com, ORCID: 0000-0002-9440-8378.

Andrii Hrimov – Applicant of Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine
e-mail: andrew.hrimov@gmail.com, ORCID: 0000-0001-5696-3779.

Vladislav Lopatka – Applicant of Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine,
e-mail: v.lopatka.v@gmail.com, ORCID: 0000-0002-1339-3849.

Olha Moroz – Senior lecturer of the Department of Theoretical and Applied Systems Engineering, V. N. Karazin Kharkiv National University, Kharkiv, Ukraine,
e-mail: o.moroz@karazin.ua, ORCID: 0000-0002-4920-4093.

Olena Tolstoluzka – Dr.Sc. (Technical), Senior Research Fellow, Professor of the Department of Theoretical and Applied Systems Engineering, V. N. Karazin Kharkiv National University, Kharkiv, Ukraine,
e-mail: elena.tolstoluzka@karazin.ua, ORCID: 0000-0003-1241-7906.