ТЕХНИЧЕСКИЕ НАУКИ
И ТЕХНОЛОГИИ

АҚПАРАТТЫҚ ЖҮЙЕЛЕР
ИНФОРМАЦИОННЫЕ СИСТЕМЫ
INFORMATION SYSTEMS

DOI 10.51885/1561-4212_2023_3_99
IRSTI 87.15.03

Y.V. Blinayeva[1], S.S. Smailova[1], A.E. Aulbekov[1], Y.F. Yaanus[2]
[1]D. Serikbayev East Kazakhstan technical university, Ust-Kamenogorsk, Kazakhstan
*E-mail: blinaeva-helen@mail.ru**
E-mail: saule_smailov@mail.ru
E-mail: aulbekov28@gmail.com
[2]Sarsen Amanzholov East Kazakhstan university, Ust-Kamenogorsk, Kazakhstan
E-mail: yana.yaanus@mail.ru

APPLICATION OF NEURAL NETWORKS FOR ATMOSPHERIC POLLUTION FORECASTING

АТМОСФЕРАНЫҢ ЛАСТАНУЫН БОЛЖАУ ҮШІН НЕЙРОНДЫҚ ЖЕЛІЛЕРДІ ҚОЛДАНУ

ПРИМЕНЕНИЕ НЕЙРОННЫХ СЕТЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ ЗАГРЯЗНЕНИЯ АТМОСФЕРЫ

Abstract. *A large number of hazardous emissions from industrial production is an environmental problem for the world cities. In the field of environmental engineering, the study of air quality and the prediction of changes in concentrations of harmful substances will make it possible to develop the right strategies for sustainable development. The paper presents the results of the development and research of the applicability of neural network modeling models for forecasting and distribution of concentrations of emissions into the atmosphere by the example of Ust-Kamenogorsk, Kazakhstan. For forecasting, the authors used an RNN network of the long short-term memory (LSTM) type, which is well adapted to learning using the tasks of classification, processing and forecasting of time series in cases when the time periods between events have different gaps. An LSTM model with 3 hidden layers and 1 output neuron in the output layer was determined to predict contamination. To determine the effectiveness of the neural network under study, the average absolute error was used as a function of losses. The authors have developed a system for modeling the process of predicting the pollution of harmful substances in the atmospheric air using data from stationary monitoring points.*

Keywords: *air pollution, forecasting, neural network modeling.*

Аңдатпа. *Аңдатпа Өнеркәсіптік өндірістердің қауіпті шығарындыларының көп болуы Әлем қалалары үшін экологиялық проблема болып табылады. Экологиялық инженерия саласында ауа сапасын зерттеу және зиянды заттар концентрациясының өзгеруін болжау тұрақты дамудың дұрыс Стратегияларын жасауға мүмкіндік береді. Мақалада Өскемен, Қазақстан қалалары мысалында атмосфераға шығарындылардың шоғырлануын болжау және бөлу үшін нейрондық желілік модельдеу модельдерінің қолданылуын әзірлеу және зерттеу нәтижелері келтірілген. Авторлар болжау үшін оқиғалар арасындағы уақыт кезеңдері әр түрлі үзілістерге ие болған жағдайда уақыттық қатарларды жіктеу, өңдеу және болжау тапсырмаларында оқуға жақсы бейімделген RNN long short-term memory (LSTM) желісін қолданды. Ластануды болжау үшін 3 жасырын қабаты бар LSTM моделі және шығыс қабатында 1 шығатын Нейрон анықталды. Зерттелетін нейрондық желінің тиімділігін анықтау үшін жоғалту функциясы ретінде орташа абсолютті қате қолданылды. Авторлар мониторингтің стационарлық нүктелерінің деректерін пайдалана отырып, атмосфералық ауадағы зиянды заттардың ластануын болжау процесін модельдеу жүйесін әзірледі.*

Түйін сөздер: *ауаның ластануы, болжау, нейрондық желіні модельдеу.*

Аннотация. *Большое количество вредных промышленных выбросов является экологической проблемой для городов всего мира. В области экологической инженерии изучение качества воздуха и прогнозирование изменения концентрации вредных веществ позволит выработать правильные стратегии устойчивого развития. В статье представлены результаты разработки и исследования применимости моделей нейросетевого моделирования для прогнозирования и распределения концентраций выбросов в атмосферу на примере города Усть-Каменогорска, Казахстан. Авторы использовали RNN сеть типа долговременной кратковременной памяти (LSTM), которая хорошо приспособлена для обучения задачам классификации, обработки и прогнозирования временных рядов, когда промежутки времени между событиями имеют различные промежутки. Для прогнозирования была определена модель LSTM с 3 скрытыми слоями и 1 нейроном в выходном слое загрязнения. Для определения эффективности исследуемой нейронной сети была рассчитана средняя абсолютная ошибка как функция потерь. Авторами разработана система моделирования процесса прогнозирования загрязнения вредных веществ в атмосферном воздухе по данным стационарных точек мониторинга.*

Ключевые слова: *загрязнение воздуха, прогнозирование, нейросетевое моделирование.*

Introduction. The problem of atmospheric air pollution and its impact on human health is one of the most important issues of scientific research in terms of importance and relevance.

Eminent air pollution negatively affects human health. The incidence of respiratory organs, endocrine system, circulatory system is increasing. There is a growing trend in the number of oncological cases, leukemia and other diseases. The situation is aggravated by the fact that many of the substances present in the atmospheric air have the so-called summation effect, when the negative impact on the human body increases with their joint presence in the air. Such substances are sulfur dioxide and hydrogen fluoride, nitrogen dioxide and carbon monoxide, etc.

Many cities have systems for monitoring the concentration of substances in the atmosphere. These systems are a set of hardware and software, the main function of which is to collect information about the state of atmospheric air, as well as to cotrol compliance with emission standards of harmful substances.

The frequency and duration of periods of increased concentration of substances in the atmospheric air depends on the mode of emission from sources, as well as on the nature of meteorological conditions affecting the level of concentration of impurities. Thus, it is necessary to identify the factors determining changes in the concentration of harmful substances when weather conditions change, and to take these conditions into account when forecasting.

One of the important means of observation is the control of the transfer of impurity flows, which is necessary to obtain information about spatial variability and to build an air pollution map. For this purpose, methods of mathematical modeling of the processes of scattering of impurities in atmospheric air are used.

The first to study the prediction of air pollution were the researchers from the USA: Badger C.M., Miller M.E., E.K. Caper, C.J. Hopper, E. Gross. Their works described a system of short-term forecasts and concluded that the main reason for the increased concentration of harmful substances is no-wind conditions and lack of precipitation. But these models did not take into account some patterns of the influence of meteorological conditions to determine the level of pollution.

In the future, the development of air pollution studies was carried out using statistical methods of research and observation. The paper [Rybak V.A. at all, 2020] describes the process of developing a hardware and software complex for mobile monitoring of the state of atmospheric air, which allows building pollution maps in real time. Of scientific and practical interest is the prediction of changes in atmospheric air pollution taking into account the direction and strength of the wind, for example, to obtain the safest route for a group of children, optimizing traffic flows, evacuation in case of technogenic accidents.

To assess the transport of pollutants in the atmospheric air in the work [Rybak V.A. at all, 2020], the OND-86 methodology, "Methodology for calculating concentrations in the atmospheric air of harmful substances contained in the emissions of enterprises," was used.

Paper [Khramtsova N.N. at all, 2009], devoted to the analysis of emissions of pollutants into the atmosphere and the organization of their control, examines the analysis of stationary and mobile sources of pollution and systematizes information about the amount of pollutants. It also offers a system of control measures for the protection of atmospheric air to determine the danger of an increase in pollutants.

The work of A.A. Muradov [Muradov A. A., 2013] analyzes the pollution of the atmosphere by mobile motor transport using the apparatus of the theory of fuzzy logic. Using the theory of fuzzy sets and the Takagi-Sugeno fuzzy control method, an approach for assessing environmental safety was proposed.

In the dissertation [Yakshina N. V., 2007] Yakshina N.V. describes the possibility of predicting the concentration of suspended solids and nitrogen dioxide in atmospheric air using neural networks, based on the data of previous values and meteorological data.

Work [Plugotarenko N. K. at all, 2012] considers the use of a neural network that allows building a predictive model of the distribution of pollutants in the atmospheric air, taking into account the speed, wind direction and air temperature.

Papers [Khramtsova N.N. at all, 2009; Muradov A. A., 2013; Yakshina N. V., 2007; Plugotarenko N. K. at all, 2012] describe various approaches to the issue of data analysis of pollutants, use methods of modeling atmospheric pollution and offer various measures for early detection of elevated concentrations. The works [Khramtsova N.N. at all, 2009; Muradov A. A., 2013] provide a retrospective analysis and do not provide prognostic information. In the material [Yakshina N. V., 2007], data are considered in the long term, without considering the possibility of obtaining predictive data on the concentration of substances in a shorter period of time. Modeling in [Plugotarenko N. K. at all, 2012] neither takes into account metric data on precipitation amounts, nor considers various types of pollutants as categorial data when modeling future values.

The papers [Xu Feng at all, 2019; Ana Russo at all, 2015] reflect the results of neural networks identifying patterns for predicting daily, weekly, and seasonal concentrations of emissions of harmful substances in the regions of Southern China and Lisbon. The results described in the papers reflect the results of the use of neural networks in the development of ensembles of neural networks with reverse propagation (BPNN) [Xu Feng at all, 2019] and a data pre-selection system [Ana Russo at all, 2015], with the selection of the most accurate parameters that allowed increasing the accuracy of forecasts of the spatial distribution of the concentration of pollutants.

The work [Bindhu Lal at all, 2012] demonstrates the results of predicting dust concentration in an open-pit coal mine using an artificial neural network. These models were developed using a multi-layer perception network, and their training is carried out using a back propagation algorithm.

The paper [Rati Wongsathan at all, 2016] provides a comparative analysis of ARIMA models and neural networks (NNs). The results of the analysis allow to conclude that the ARIMA model may be inadequate for a complex regular problem, while the NNs model can reveal the correlation of a nonlinear pattern well. To improve the forecasting efficiency for achieving high accuracy, the authors developed a hybrid model of ARIMA and NNs - hARIMA-NNs. The experimental results showed an improvement in the prediction accuracy of the hARIMA-NNs model compared to ARIMA and NNs by an average of 65% and 50%, respectively.

Work [Junbeom Park at all, 2021] demonstrates an algorithm based on long-term - short-term memory (LSTM) models and artificial neural network (ANN). The most characteristic advantage of the model proposed in the paper is that the efficiency of PM concentration prediction has been improved by choosing a more efficient model between ANN and LSTM. The experimental results showed that the model demonstrates a 1-3% higher F1-score, which is a measure combining accuracy and responsiveness. It is usually called the harmonic mean of two values.

The paper [Akibu Mahmoud Abdullah at all, 2021] presents the results of operation of an optimized artificial neural network (OANN) developed to improve the existing artificial neural network (ANN) by updating the initial weights in the network using a genetic algorithm (GA). The OANN model was implemented to predict the concentration of CO, NO, NO2 and NOx pollutants produced by motor vehicles in Kuala Lumpur, Malaysia.

In 2003 J. Kukkonen conducted a study [Jaakko Kukkonen at all, 2003] to predict the concentration of solids using 5 different models. The results showed that neural network models work better than linear models.

Perez P. et al [Perez, P. at all, 2000] describe the construction of a neural network prediction model for solid particles whose size does not exceed 2.5mm. 3 predictive models were developed: neural network, linear and persistent. The average absolute error ranged from 30 to 60%. It was also found that depending on weather conditions, the concentration of solids negatively correlates with wind speed and humidity.

In a review of the use of neural networks in the field of problems related to the atmosphere, Gardner M. and Dorling S. [M.W. Gardner at all, 2000] compare different approaches that have been applied to various atmospheric indicators and time intervals. In this paper they conclude that neural networks usually give the same or better results than linear methods. Thus, neural network methods allow modeling data when the use of classical modeling methods is not possible.

The purpose of this study was to develop and study the applicability of neural network modeling models for forecasting and distribution of atmospheric emission concentrations in the urban environment. The input data on the type of substance and the location of stationary monitoring stations were considered as categorial for the construction of a predictive model.

Materials and methods of research. There are various forecasting methods, the purpose of which is to perform a sequence of actions for obtaining a model that adequately describes the process under study. In practice, regression models, autoregressive models, and exponential smoothing models are used. Neural network modeling methods are currently the most promising. One of the important advantages of artificial neural networks is the ability to learn based on the current sample; it is also one of the few approaches that uses time dependencies between samples.

Neural network models. An artificial neural network is a mathematical model, as well as software and hardware, it is built on the analogue of a biological neural network – a collection of neurons. Neural networks allow reproducing sequences of any complexity.

The neuron model can be described by a pair of equations:

$$\boldsymbol{U(t) = \sum_{i=1}^{m} w_i * Z(t-1) + b} \qquad (1)$$
$$\boldsymbol{Z(t) = f(U(t))}$$

where Z(t-1) , … , Z(t-m) − input signals; wi − synaptic weights of a neuron; b − limit; $f(U(t))$ − activation function.

With the help of neural networks, it is possible to simulate the nonlinear dependence of the future value of a time series on its actual values and on external factors. The nonlinear dependence is determined by the network structure and activation function.

When training the model, a set of weighting coefficients is searched for, at that the input signal is converted into an output after passing through the neural network. To do this, it is necessary to determine the set of input signals by which the training takes place. After the learning process, when the correct results for the training sample are obtained using the model, the network can be considered trained and used in practice. But before that, it is necessary to evaluate the quality of its work on a test sample, i.e. based on a set of input signals and the expected output data, according to which it is possible to assess the quality of the network.

For forecasting, the authors used an RNN network of the long short-term memory (LSTM) type, which is well adapted to learning on the tasks of classification, processing and forecasting of time series in cases when the time periods between events have different gaps.

An LSTM model with 3 hidden layers and 1 output neuron in the output layer was determined to predict contamination. To determine the effectiveness of the neural network under study, the average absolute error was used as a loss function and adaptive moment estimation (adam) as a method for optimizing the neural network.

To train the model, approximately 50 epochs with 70 iterations were performed, using the error propagation learning algorithm. Figure 1 shows the error values during network training.

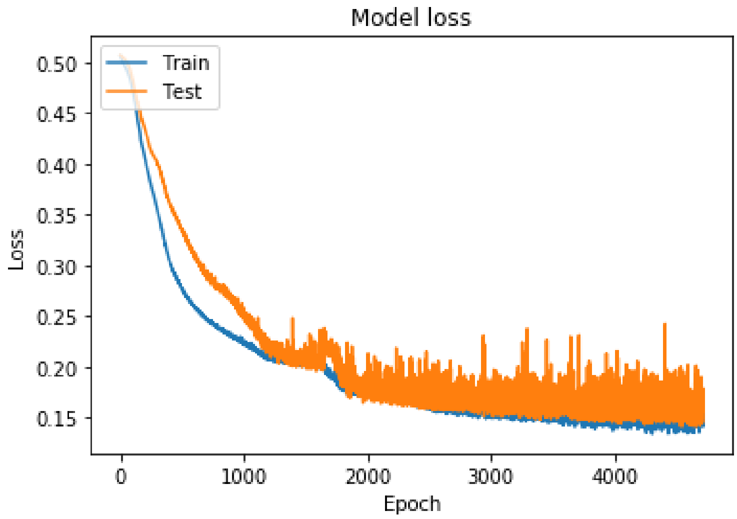

Figure 1. The error values during network training

After training the model, forecasting was performed on a test data set with subsequent evaluation of the model error. The simulation results showed that the use of the selected methods allows achieving satisfactory results. The use of neural networks makes it possible to build the most accurate predictive model of pollution in the atmospheric air, which will ensure the preparation of forecasts for timely response and making the necessary decisions. The main criteria for choosing the method is the value of the root-mean-square error, the best result of which was achieved with neural network modeling.

The next step is to correct and adjust the structure of the neural network to determine the optimal model that allows obtaining satisfactory results.

Results and discussion.

Organization of data collection

The research covered the data on the concentration of pollution in the atmospheric air of Ust-Kamenogorsk, as well as hydrometeorological observations, including measurements of temperature, pressure and humidity, wind speed and direction, and precipitation. Pollution monitoring was carried out at intervals of 20 minutes, and meteorological data - 10 minutes.

During the data collection process, it was decided to use MySQL as a local data bank, since it was planned to implement a data analysis application in Python. The number of monitoring system records was 877099 rows, which is not a large amount of data for modern database management systems, but it also depends on the hardware and software configuration of the database.

Data preparation

The initial step in data analysis is the initial data collection. It includes operations such as loading data, searching for incorrect, empty and various non-valid values. Then a decision is made on how to process the information correctly in this situation, for example, one option is to completely delete a row with invalid values.

The first stage performs loading data into memory for further processing. The next step is data filtering. At this stage, the data will be cleared from those in which there are no values; invalid values received from monitoring system devices, such as negative values, as well as those that repeatedly exceed the maximum permissible concentration will be eliminated. A brief summary, the approximate content of the training data, is shown in Figure 2.

	id	substance	point	value	time	temp	wind_dir	wind_speed	humidity	prec	prec_intens	pressure	Longi	Lati	PDK_MP	PDK_DD
0	9052365	21	1008	0.097656	2018-09-12 20:40:00	3.5	32.0	0.5	64.0	0.0	0.0	990.0	82.73336	50.02668	0.2	0.040
1	9052359	21	1007	0.053467	2018-09-12 20:40:00	3.5	32.0	0.5	64.0	0.0	0.0	990.0	82.62397	49.99991	0.2	0.040
2	9052361	23	1008	0.073730	2018-09-12 20:40:00	3.5	32.0	0.5	64.0	0.0	0.0	990.0	82.73336	50.02668	0.5	0.125
3	9052360	23	1007	0.013794	2018-09-12 20:40:00	3.5	32.0	0.5	64.0	0.0	0.0	990.0	82.62397	49.99991	0.5	0.125
4	9052350	23	1001	0.004791	2018-09-12 20:40:00	3.5	32.0	0.5	64.0	0.0	0.0	990.0	82.60972	49.97353	0.5	0.125

Figure 2. Brief summary of the data

One of the important stages is the processing of categorial (attribute) data. Such data does not show a quantitative measurement of data, but a qualitative characteristic, i.e. belonging to some category. The attributes that have been subjected to this transformation are the type of substance and the monitoring station. These attributes have been converted into the number of variants of the values of this attribute. 9 values with the station ID appeared for the monitoring station, in which the value 1 shows the station from which the value was taken, and the value 0 indicates that the data does not relate to this station. For each type of substance, its own attribute was also defined, in which a value of 0 indicates that the data belong to a different type of substance, and a value other than zero indicates the concentration value of this substance. It is also necessary to exclude some attributes that do not have an impact when training the model. Such attributes are: identifiers of the substance and the monitoring post, MPC values, and concentration value.

The next step is to convert the original time series data array into a format suitable for training. To do this, it is necessary to normalize the input data. This is due to the fact that data differ from each other in absolute values. Data normalization allows converting the original numeric values of variables into identical application domain, which will allow them to be used in the same neural network model. In practical implementation, the MinMaxScaler function of the sklearn library was used, which performs scaling and transformation for each individual attribute in a given range from 0 to 1.

After scaling the data, the transformation was performed into a single structure containing 24 columns. Figure 3 shows the resulting data set after conversion.

```
   39[7](t-1)  37[8](t-1)  1009[9](t-1)  1008[10](t-1)        ...          \
1         0.0         0.0           0.0            1.0        ...
2         0.0         0.0           0.0            1.0        ...
3         0.0         0.0           0.0            1.0        ...
4         0.0         0.0           0.0            1.0        ...
5         0.0         0.0           0.0            1.0        ...

   1003[15](t-1)  1002[16](t-1)  1001[17](t-1)  value[18](t-1)  temp[19](t-1)  \
1            0.0            0.0            0.0        0.550781           -1.5
2            0.0            0.0            0.0        0.483398           -2.0
3            0.0            0.0            0.0        0.628906           -2.5
4            0.0            0.0            0.0        0.533203           -4.0
5            0.0            0.0            0.0        0.841797           -5.5

   wind_dir[20](t-1)  wind_speed[21](t-1)  humidity[22](t-1)  \
1              229.0             5.500000               53.0
2              231.0             7.000000               45.0
3              248.0             4.000000               46.0
4              229.0             8.500000               51.0
5              243.0             5.890625               54.0

   pressure[23](t-1)  next_val[24](t-1)
1              972.0           0.483398
2              972.0           0.628906
3              974.0           0.533203
4              974.0           0.841797
5              976.0           0.603516

[5 rows x 24 columns]
```

Figure 3. Normalized data set

In the next step, the original data set must be divided into several datasets. 80% of the initial data was selected for training and the following sets were obtained as a result:

– data set for training;

– a set of data with training validation to assess the quality of network learning in the training process;

– data set for testing;

– a set of data from a testing check to assess the quality of network learning after completion of training.

Implementation of the intelligent module

The selection of the model structure that will provide satisfactory results was carried out using Jupiter Notebook. The possibility of interactive selection of model parameters was implemented with the help of the Ipywidgets library. Figure 4 shows a form for entering model parameters for training.

In practice, the method which is often used is when the learning rate is not a constant throughout the learning process, but decreases linearly with an increase in the number of iterations. At the initial steps of the algorithm, the weights of neurons in the network are far from optimal and therefore they can be changed to larger values. When approaching the desired values, the correction step decreases for more precise adjustment. Table 1 shows the characteristics of training the model at different speeds.

Figure 4. Interactive form for entering model parameters

Table 1. The characteristics of the model training at different speeds

Learning rate	0.01	0.05	0.1	0.5	1
Learning error	0.2736	0.1429	0.2432	0.1598	0.173
Model accuracy	0.7500	0.899	0.6850	0.834	0.850

When training the model, a comparison of different configurations was performed. Table 2 shows the results of comparing different configurations of the neural network model obtained during the study.

Table 2. Comparison of different configurations of the neural network model

Network structure	Number of epochs	Number of iterations	Training error	Testing error
1) Layers: 3, number of neurons in the layer: 23, activation function of the output layer: sigmoidal, error function: absolute deviation.	4000	5000	0.843	1.38
2) Layers: 3, number of neurons in the layer: 23, activation function of the output layer: truncated linear transformation, error function: absolute deviation.	4000	10000	0.19	0.383
3) Layers: 4, number of neurons in the layer: 23, activation function of the output layer: truncated linear transformation, error function: absolute deviation.	6000	15000	0.18	0.406
4) Layers: 4, number of neurons in the layer: 30, activation function of the output layer: truncated linear transformation, error function: absolute deviation.	6000	20000	0.182	0.36

End of table 2

5) Layers: 3, number of neurons in layers: 14,15,25; output layer activation function: truncated linear transformation, error function: absolute deviation.	10000	35000	0.173	0.33
6) Layers: 4, number of neurons in layers: 15,20,25; output layer activation function: truncated linear transformation, error function: absolute deviation.	10000	40000	0.175	0.38
7) Layers: 3 (1 LSTM layer), error function: absolute deviation	1500	5000	0.008	0.005
8) Layers: 3 (1 LSTM layer), regularization method: exclusion of 10% of neurons, error function: absolute deviation	1000	5000	0.0035	0.005

When using a long short-term memory (LSTM) type network to predict the level of carbon monoxide concentration, better indicators were demonstrated, since such networks are well adapted to learning on series prediction tasks in cases where the time periods between events have different gaps. When training a model to predict time series, the main approach is not to increase the accuracy of training, but to reduce the value of the error function.

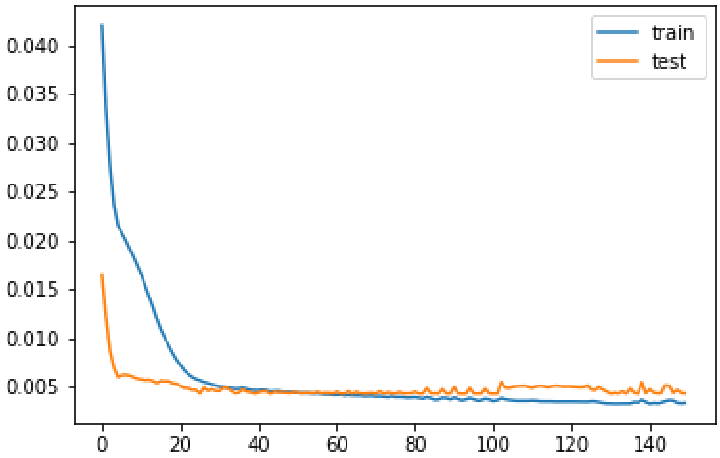

Figure 5. The value of the error during model training

Figure 5 shows the change in the value of the error function during the model training process.

The results of modelling showed that the use of the selected methods makes it possible to achieve satisfactory results. The application of the model with the use of LSTM neural networks enables building the most accurate predictive model of pollution in the atmospheric air, which will ensure the preparation of forecasts for timely response and making necessary decisions.

Generalization of the resulting model

After receiving the trained model, it is possible to investigate its structure. Figure 6 provides summary information that shows the number of layers and the order they are arranged, the format the data has at the output of the layer, the number of weights (parameters) as in each layer, so for the entire model.

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_7 (Dense)              (None, 15)                360

dense_8 (Dense)              (None, 19)                304

dense_9 (Dense)              (None, 25)                500

dense_10 (Dense)             (None, 24)                624

dense_11 (Dense)             (None, 25)                625

dense_12 (Dense)             (None, 1)                 26
=================================================================
Total params: 2,439
Trainable params: 2,439
Non-trainable params: 0
_________________________________________________________________
None
```

Figure 6. Summary of the parameters of the resulting model

When studying the structure of the model, it was determined that the layers have the correct order, and the models are connected as required. Besides, a brief summary and a diagram confirmed that the format of input and output values meets expectations. The summary also shows that there are no unused parameters, which means that no excessive number of parameters was set.

The process of making a forecast

To achieve this goal, the authors developed a system for modeling the process of predicting the pollution of harmful substances in the atmospheric air using data from stationary monitoring points by the example of Ust-Kamenogorsk, East Kazakhstan. It uses the method of neural networks to obtain predictive data on the content of pollutants.

Figure 7 shows the architecture of the urban air pollution data analysis system.

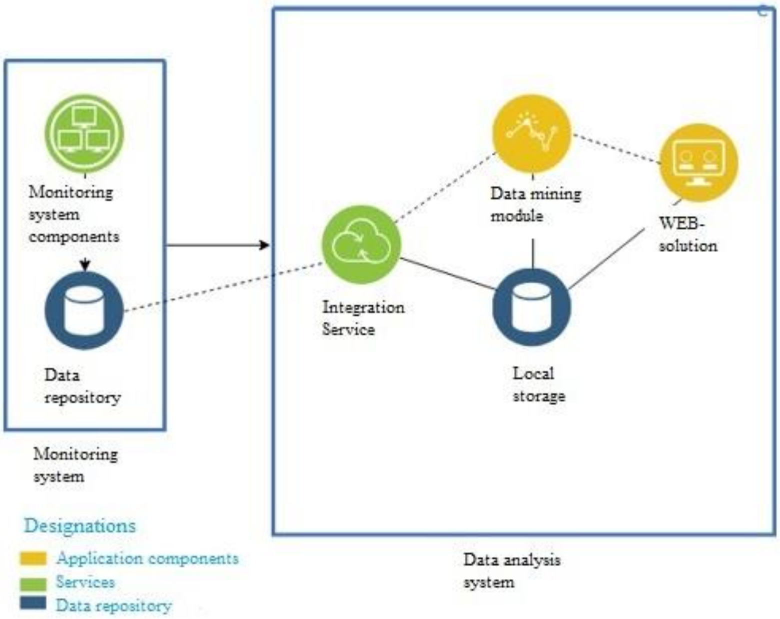

Figure 7. Architecture of the urban air pollution data analysis system

Visualization of the received data

Data visualization makes it possible to present the results in the simplest and most visual form. The module is a web application implemented in the Microsoft Visual Studio Community Edition 2017 environment using the web application template ASP.NET.

The main page displays the table of the latest data obtained in the forecasting process for each of the monitoring station areas. An example of data display is shown in Figure 8. It displays the following information:

– the location where the concentration was calculated;
– the time the forecast was made for;
– the calculated concentration value;
– the maximum one-time MPC;
– the ratio of the estimated value to the MPC.

Forecast of concentrations of pollutants in the atmospheric air of Ust-Kamenogorsk

Substance	Forecast time	Value	MPCms	Value / MPC
NO2	11.11.2018 04:20	0,0125	0,2	0,06
SO2	11.11.2018 04:20	0,0076	0,5	0,02
CO	11.11.2018 04:20	0,0084	5	0,00
HCL	11.11.2018 04:20	0,0080	0,2	0,04
HCOH	11.11.2018 04:20	0,0080	0,035	0,23
CXHY	11.11.2018 04:20	0,0080	100	0,00

Figure 8. Example of displaying predictive values

Figure 9 shows information about the total impact of substances. The information is calculated according to the formula (2).

$$\frac{C_1}{\mathrm{MPC}_1}+\frac{C_2}{\mathrm{MPC}_2}+\frac{C_3}{\mathrm{MPC}_3}\leq 1 \qquad (2)$$

This formula describes the case when simultaneously in the air there are the substances that have a cumulative (additive) effect. In such a situation, the sum of their concentrations should not be greater than 1 according to the following expression, where C_i is the concentration value, MPC_i is the maximum permissible concentration value.

The output information in this case is:

– the location where the measurements were made;
– the substances having a total effect;
– the time this value was recorded at;
– the value of the total impact coefficient.

The information about the obtained forecast values of the concentration of pollutants in the atmospheric air is displayed on the map of Ust-Kamenogorsk (Figure 10) using the Follium library. The concentration value is displayed in a gradient from green to red (0.5-0.8 – green, 0.8-0.87 – yellow, 0.87-0.95 – orange, over 0.95 – red).

Cumulative exposure to substances

Address	Substance	Forecast time	Cumulative impact coefficient
South of the Northern Industrial Zone, 14 Gastello St., school	Nitrogen dioxide, Sulfur dioxide, Formaldehyde	01.10.2018 02:00	1,5070
South of the Northern Industrial Zone, 14 Gastello St., school	Nitrogen dioxide, Sulfur dioxide, Formaldehyde	01.10.2018 03:00	1,5049
Mirny, 59 Pogranichnaya St., Oskemen Vodokanal	Nitrogen dioxide, Sulfur dioxide, Formaldehyde	01.10.2018 04:00	1,3779

Figure 9. Information on the total impact of substances

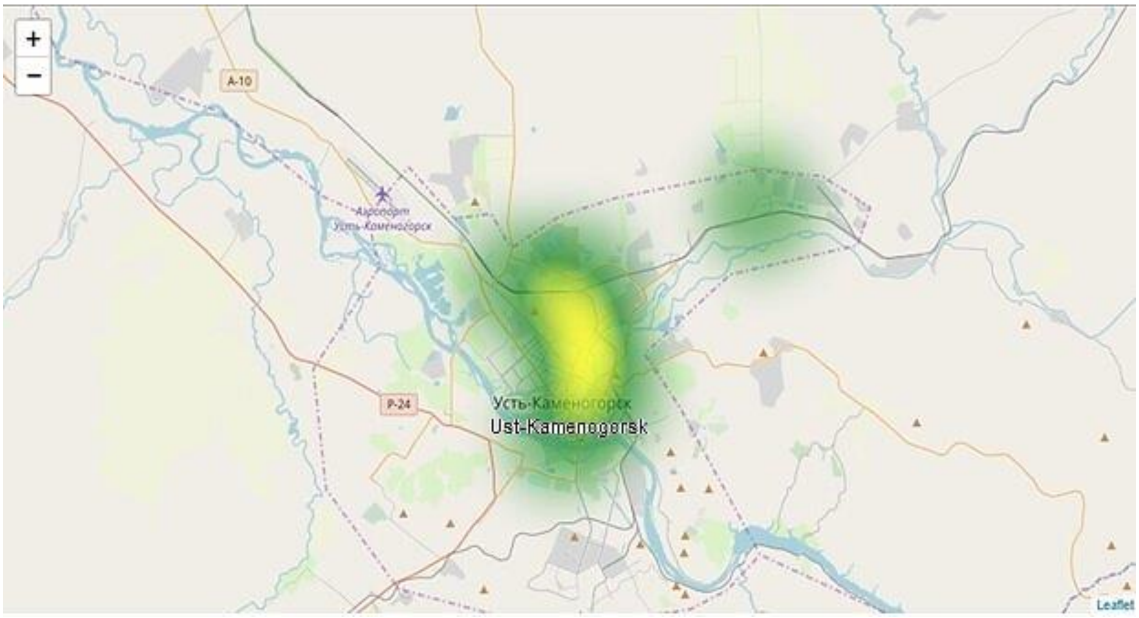

Figure 10. Heat map of predicted concentration values

Conclusions. The paper proposes a system for analyzing data on emissions of pollutants into the atmosphere. The structure of the neural network for predicting the distribution of pollutants was determined. The study of the model structure showed that the layers have the correct order, the format of the input and output values corresponds to the expected one, and there are no unused parameters in the model.

An environmental monitoring system has been developed. It includes a data collection subsystem, a forecasting module responsible for the formation and training of a neural network and calculating the prediction result, and a web application for displaying and visualizing information about pollutant emissions.

The application of the model using LSTM neural networks made it possible to build the most accurate predictive model of pollution in the atmospheric air, which let predict and make the necessary decisions.

Список литературы

1. Рыбак В.А., Рябычина О.П. Система экологического мониторинга атмосферного воздуха. Doklady BGUIR, 2020, VOL. 18, NO. 4. https://doi.org/10.35596/1729-7648-2020-18-4-36-43
2. Храмцова Н.Н., Бодруг Н.С. Анализ выбросов загрязняющих веществ в атмосферу и организация их контроля. Амурский государственный университет, г. Благовещенск. – Problemele energetici regionale, 2(10). 2019. https://journal.ie.asm.md/en/contents/elektronnyij-zhurnal-n-210-2019
3. Мурадов А. А. Анализ загрязнения атмосферы города выбросами автотранспорта методом нечеткой логики // Стратегия устойчивого развития регионов России. 2018. №18. URL: https://cyberleninka.ru/article/n/analiz-zagryazneniya-atmosfery-goroda-vybrosami-avtotransporta-metodom-nechetkoy-logiki (дата обращения: 25.03.2022).
4. Якшина Н. В. Нейросетевое моделирование процессов загрязнения окружающей среды: диссертация на соискание степени кандидата физико-математических наук: 03.00.16. - Екатеринбург, 2019. - 148 с.: ил.
5. Плуготаренко Н. К., Варнавский А. Н. Применение нейронных сетей для построения модели прогнозирования состояния городской воздушной среды // ИВД. 2021. №4-2. URL: https://cyberleninka.ru/article/n/primenenie-neyronnyh-setey-dlya-postroeniya-modeli-prognozirovaniya-sostoyaniya-gorodskoy-vozdushnoy-sredy (дата обращения: 25.03.2022).
6. Xu Feng, Tzung-May Fu, Hansen Cao, Heng Tian, Qi Fan, Xiaoyang Chen. Neural network predictions of pollutant emissions from open burning of crop residues: Application to air quality forecasts in southern China. Atmospheric Environment, volume 204, (2019). P. 22–31. https://doi.org/10.1016/j.atmosenv.2019.02.002.
7. Ana Russo, Pedro G. Lind, Frank Raischel, Ricardo Trigo, Manuel Mendes. Neural network forecast of daily pollution concentration using optimal meteorological data at synoptic and local scales. Atmospheric Pollution Research, volume 6, (2019). P. 540 – 549. doi: 10.5094/APR.2015.060.
8. Bindhu Lal, Sanjaya Shankar Tripathy. Prediction of dust concentration in open cast coal mine using artificial neural network. Atmospheric Pollution Research, volume 3 (2019). P. 211-218. doi: 10.5094/APR.2012.023.
9. Rati Wongsathan, Isaravuth Seedadan. A hybrid ARIMA and Neural Networks model for PM-10 pollution estimation: The case of Chiang Mai city moat area. Procedia Computer Science, vol. 86, (2016). P. 273 – 276. doi: 10.1016/j.procs.2016.05.057.
10. Junbeom Park, Seongju Chang. A Particulate Matter Concentration Prediction Model Based on Long Short-Term Memory and an Artificial Neural Network. International Journal of Environmental Research and Public Health. 2021, 18 (13), 6801. https://doi.org/10.3390/ijerph18136801.
11. Akibu Mahmoud Abdullah, Raja Sher Afgun Usmani, Thulasyammal Ramiah Pillai, Mohsen Marjani, Ibrahim Abaker Targio Hashem. An Optimized Artificial Neural Network Model using Genetic Algorithm for Prediction of Traffic Emission Concentrations. International Journal of Advanced Computer Science and Applications, Vol. 12, No. 6, 2021. P. 794 – 803. DOI: 10.14569/IJACSA.2021.0120693.
12. Jaakko Kukkonen, Leena Partanen, Ari Karppinen, Juhani Ruuskanen, Heikki Junninen, Mikko Kolehmainen, Harri Niska, Stephen Dorling, Tim Chatterton, Rob Foxall, Gavin Cawley. Extensive evaluation of neural network models for the prediction of NO2 and PM10 concentrations, compared with a deterministic modelling system and measurements in central Helsinki, Atmospheric Environment, Volume 37, Issue 32, 2003, Pages 4539-4550, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(03)00583-1.
13. Perez, P., Trier, A., and Reyes, J. (2000). Prediction of PM2.5 concentrations several hours in advance using neural networks in Santiago, Chile, Atmospheric Environment, Volume 34, Issue 8, 2000, Pages 1189-1196, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(99)00316-7.
14. M.W. Gardner, S.R. Dorling. Statistical surface ozone models: an improved methodology to account for non-linear behaviour, Atmospheric Environment, Volume 34, Issue 1, 2000, Pages 21-34, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(99)00359-3
15. Ходакова Анна Геннадьевна, Савицкая Татьяна Вадимовна Разработка нейросетевой модели прогнозирования загрязнения атмосферного воздуха источниками выбросов предприятия // Успехи в химии и химической технологии. 2020. №6 (229). URL: https://cyberleninka.ru/article/n/razrabotka-neyrosetevoy-modeli-prognozirovaniya-zagryazneniya-atmosfernogo-vozduha-istochnikami-vybrosov-predpriyatiy (дата обращения: 13.10.2022).

References

1. Rybak V.A. Ryabychina O.P. Sistema ekologicheskogo monitoringa atmosfernogo vozdukha. Doklady BGUIR, 2020, VOL. 18, NO. 4. https://doi.org/10.35596/1729-7648-2020-18-4-36-43
2. Khramtsova N.N.. Bodrug N.S. Analiz vybrosov zagryaznyayushchikh veshchestv v atmosferu i organizatsiya ikh kontrolya. Amurskiy gosudarstvennyy universitet. g. Blagoveshchensk. – Problemele energetici regionale, 2(10). 2019. https://journal.ie.asm.md/en/contents/elektronnyij-zhurnal-n-210-2019
3. Muradov A.A. Analiz zagryazneniya atmosfery goroda vybrosami avtotransporta metodom nechetkoy logiki // Strategiya ustoychivogo razvitiya regionov Rossii. 2018. №18. URL: https://cyberleninka.ru/article/n/analiz-zagryazneniya-atmosfery-goroda-vybrosami-avtotransporta-metodom-nechetkoy-logiki (дата обращения: 25.03.2022).
4. Yakshina N. V. Neyrosetevoye modelirovaniye protsessov zagryazneniya okruzhayushchey sredy: dissertatsiya na soiskaniye stepeni kandidata fiziko-matematicheskikh nauk: 03.00.16. - Ekaterinburg, 2019. – 148 с.: il.
5. Plugotarenko N.K. Varnavskiy A.N. Primeneniye neyronnykh setey dlya postroyeniya modeli prognozirovaniya sostoyaniya gorodskoy vozdushnoy sredy // IVD. 2021. №4-2. URL: https://cyberleninka.ru/article/n/primenenie-neyronnyh-setey-dlya-postroeniya-modeli-prognozirovaniya-sostoyaniya-gorodskoy-vozdushnoy-sredy (дата обращения: 25.03.2022).
6. Xu Feng, Tzung-May Fu, Hansen Cao, Heng Tian, Qi Fan, Xiaoyang Chen. Neural network predictions of pollutant emissions from open burning of crop residues: Application to air quality forecasts in southern China. Atmospheric Environment, volume 204, (2019). P. 22–31. https://doi.org/10.1016/j.atmosenv.2019.02.002.
7. Ana Russo, Pedro G. Lind, Frank Raischel, Ricardo Trigo, Manuel Mendes. Neural network forecast of daily pollution concentration using optimal meteorological data at synoptic and local scales. Atmospheric Pollution Research, volume 6, (2019). P. 540 – 549. doi: 10.5094/APR.2017.060.
8. Bindhu Lal, Sanjaya Shankar Tripathy. Prediction of dust concentration in open cast coal mine using artificial neural network. Atmospheric Pollution Research, volume 3 (2019). P. 211-218. doi: 10.5094/APR.2012.023.
9. Rati Wongsathan, Isaravuth Seedadan. A hybrid ARIMA and Neural Networks model for PM-10 pollution estimation: The case of Chiang Mai city moat area. Procedia Computer Science, vol. 86, (2016). P. 273 – 276. doi: 10.1016/j.procs.2016.05.057.
10. Junbeom Park, Seongju Chang. A Particulate Matter Concentration Prediction Model Based on Long Short-Term Memory and an Artificial Neural Network. International Journal of Environmental Research and Public Health. 2021, 18 (13), 6801. https://doi.org/10.3390/ijerph18136801.
11. Akibu Mahmoud Abdullah, Raja Sher Afgun Usmani, Thulasyammal Ramiah Pillai, Mohsen Marjani, Ibrahim Abaker Targio Hashem. An Optimized Artificial Neural Network Model using Genetic Algorithm for Prediction of Traffic Emission Concentrations. International Journal of Advanced Computer Science and Applications, Vol. 12, No. 6, 2021. P. 794 – 803. DOI: 10.14569/IJACSA.2021.0120693.
12. Jaakko Kukkonen, Leena Partanen, Ari Karppinen, Juhani Ruuskanen, Heikki Junninen, Mikko Kolehmainen, Harri Niska, Stephen Dorling, Tim Chatterton, Rob Foxall, Gavin Cawley. Extensive evaluation of neural network models for the prediction of NO2 and PM10 concentrations, compared with a deterministic modelling system and measurements in central Helsinki, Atmospheric Environment, Volume 37, Issue 32, 2003, Pages 4539-4550, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(03)00583-1.
13. Perez, P., Trier, A., and Reyes, J. (2000). Prediction of PM2.5 concentrations several hours in advance using neural networks in Santiago, Chile, Atmospheric Environment, Volume 34, Issue 8, 2000, Pages 1189-1196, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(99)00316-7.
14. M.W. Gardner, S.R. Dorling. Statistical surface ozone models: an improved methodology to account for non-linear behaviour, Atmospheric Environment, Volume 34, Issue 1, 2000, Pages 21-34, ISSN 1352-2310, https://doi.org/10.1016/S1352-2310(99)00359-3
15. Hodakova ZHanna Gennad'evna, Savickaya Tat'yana Vadimovna Razrabotka nejrosetevoj modeli prognozirovaniya zagryazneniya atmosfernogo vozduha istochnikami vybrosov predpriyatij // Uspekhi v himii i himicheskoj tekhnologii. – 2020. № 6 (229). – URL: https://cyberleninka.ru/article/n/razrabotka-neyrosetevoy-modeli-prognozirovaniya-zagryazneniya-atmosfernogo-vozduha-istochnikami-vybrosov-predpriyatiy (data obrashcheniya: 13.10.2022).