Prediction of CO levels in the air based on UV index using artificial intelligence algorithms*

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Abstract

This paper investigates the problem of predicting the concentration of carbon monoxide (CO) in the atmospheric air, taking into account the intensity of ultraviolet (UV) radiation, by applying artificial intelligence methods, in particular neural networks. The work is based on the hypothesis that there is an inverse correlation between the intensity of UV radiation and the level of CO in the air, which is explained by photochemical processes of splitting carbon compounds under the influence of solar radiation. To build the model, a neural network (MLP) was used, which was trained on the basis of real environmental data, including daily UV index values. It is important to prepare the input data, normalize it, choose the model architecture, number of layers and neurons. In particular, the quality of the predictive model was assessed using the MAPE metric and the determination coefficient R^2. In general, the results confirm the high efficiency of the model in predicting CO concentrations, which indicates the prospects of implementing neural network approaches in environmental monitoring and early warning systems for air pollution.

Keywords

air quality, carbon monoxide, prediction, artificial intelligence, machine learning

1. Introduction

The problem of air pollution is one of the most pressing environmental challenges of our time, as air quality directly affects human health, the environment and the climate. According to the World Health Organization, air pollution is one of the leading causes of premature mortality in the world. The main sources of pollution are road transport, industrial plants, and the burning of fossil fuels and biomass. Emissions of toxic gases in cities lead to a deterioration of the atmosphere and increased risks for the population. One of the most dangerous components of pollution is carbon monoxide (CO), which belongs to the group of major air pollutants along with particulate matter (PM2.5, PM10), ozone (O_3), nitrogen dioxide (NO_2), and other gases. Carbon monoxide is a colorless, odorless gas formed during the incomplete combustion of organic fuels, and a significant portion of it is emitted into the atmosphere by road transport, especially in conditions of heavy traffic and poor technical condition of engines. In particular, when CO enters the human body, it binds to blood hemoglobin to form carboxyhemoglobin, which prevents the transport of oxygen to tissues. This leads to hypoxia, which is manifested by symptoms of poisoning, namely, shortness of breath, fatigue, dizziness, and nausea. At high CO concentrations, there is a real threat to life, as irreversible damage to the central nervous system or even death is possible. Therefore, monitoring of CO concentrations in the air is a necessary measure for the timely detection of dangerous levels of this gas [1-2]. In particular, in the city of Ternopil, which has no large industrial enterprises, the main source of air pollution is road transport. Increased traffic intensity, especially during rush

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hours, causes CO levels to rise in the ground layer. According to environmental monitoring data, a significant proportion of CO concentration measurements in the region exceeds the maximum permissible standards, namely, in some studies, up to 37.5% of air samples had CO concentrations above the standard [3]. This emphasizes the urgency of the task of predicting and reducing the CO content in the city's atmosphere.

In Ukraine, since 2017, the international program “Clean Air for Ukraine” has been implemented in cooperation with the Czech NGO Arnika and the Ukrainian NGO Free Arduino [4]. One of the program's results is the creation of the country's largest network of public air quality monitoring stations, EcoCity.

The AirFresh station models operate in real time, measuring the concentrations of key pollutants (PM_1, PM_2.5, PM_10, CO, NO_2, O_3, etc.). Therefore, one of these stations was installed on the territory of Ternopil National Technical University named after Ivan Puluj in cooperation with the EcoCity project. In addition, we have developed a portable station for measuring the UV index level based on the Arduino platform and an ultraviolet radiation sensor. When monitoring data from both stations, it was found that the CO level increases during periods of high traffic load and decreases during intense solar radiation. This suggests that ultraviolet radiation (UV) contributes to the photochemical decomposition of CO. Thus, during the daytime, when the UV Index is high, the concentration of carbon monoxide decreases, which confirms the existence of an inverse relationship between UV and CO. [5]. In general, intense sunlight contributes to the natural purification of the atmosphere from carbon monoxide. On the other hand, UV rays are involved in the formation of photochemical smog, affecting the concentration of ozone and other secondary pollutants. Therefore, the study of the relationship between UV radiation and CO concentration is relevant for understanding the processes of atmospheric self-purification and can be the basis for air quality predicting models.

Traditional approaches to predicting pollutant levels are based on statistical regression models or physicochemical calculations, but the accuracy of such deterministic methods is often insufficient due to the complexity of the processes of transport and transformation of impurities in the urban atmosphere. Instead, machine learning methods are increasingly being used in air quality modeling tasks, demonstrating better accuracy than classical models [6]. In general, neural networks, in particular multilayer perceptrons, are able to detect nonlinear relationships between environmental parameters and impurity concentrations and generalize information from the training set, forming functional relationships even if the nature of these relationships is not known. Unlike linear regression, neural networks are better at interpolating complex relationships and taking into account the nonlinear effects of meteorological factors. In particular, in [7], the authors successfully built a model based on a neural network to predict NO_2 concentrations based on meteorological parameters. This approach aligns with recent studies on the stability and dynamics of neural networks with time delays, where exponential estimation techniques have been applied to assess convergence rates in discrete-delay models [8,9]. This emphasizes the potential of using artificial intelligence for environmental monitoring even in conditions of limited sensors and resources. While the authors of [10] propose a hybrid model based on convolutional neural networks (CNN) and recurrent networks (LSTM) for detailed air pollution predicting. The authors of [11] also investigated the use of deep learning models for short-term air quality predicting based on meteorological and anthropogenic data. In [12], a model based on LSTM and auto-encoders is proposed to detect anomalies in indoor air quality data. In particular, the authors of [13] present a global analysis of changes in $PM_{2.5}$ with high resolution, which allows to assess the impact on public health in different regions of the world. In addition, the authors of [14] developed an approach to monitoring fine particulate matter (PM_1) based on high-resolution satellite data.

It is known that neural networks demonstrate high prediction accuracy not only in environmental monitoring but also in other fields of science and technology. In particular, in the field of mechanics, neural networks have been used to estimate the residual life of structural elements, which has made it possible to improve the accuracy of the prediction of operational reliability [15]. In materials science, machine learning methods have been used to model the thermal conductivity of epoxy resin [16], to study the tribotechnical characteristics of epoxy composites, and to build models of the mechanical properties of composites modified by electric spark water hammer [17,18]. In information technology, neural networks have been used to study the architecture of network platforms for monitoring objects in cyber-physical systems of smart cities [19], to classify DDoS attacks using machine learning algorithms [20], and to detect malicious network traffic, including that generated by IoT devices, using intelligent models [21]. Thus, the versatility of neural networks, their ability to detect hidden nonlinear patterns in large data sets, and their high predictive power confirm the feasibility of their application in a wide range of scientific tasks.

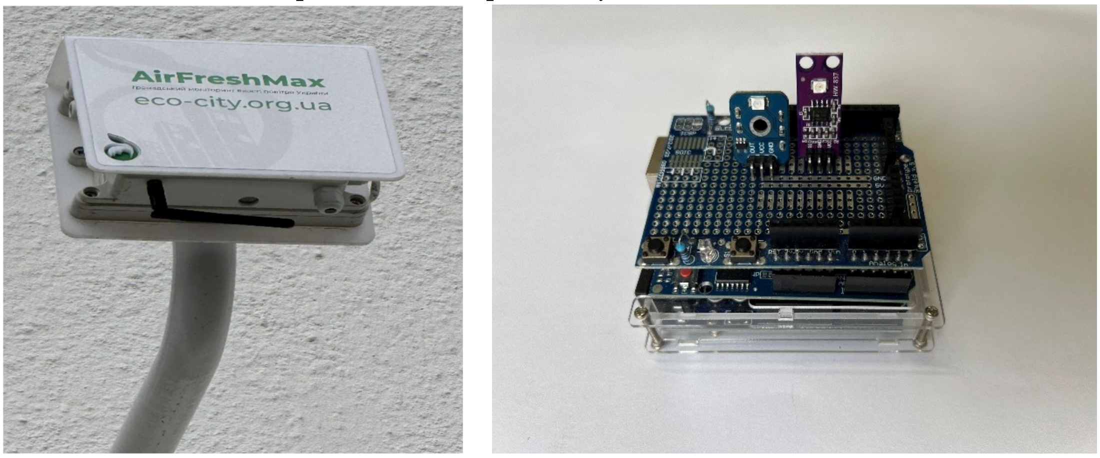
The purpose of this paper is to develop and evaluate a model based on an artificial neural network for predicting CO concentration based on the UV index, which is an indicator of solar radiation intensity that indirectly affects the rate of photochemical decomposition of CO. In particular, the relationship between UV level and CO concentration in the atmosphere is analyzed, and the accuracy of the prediction is compared with traditional models, such as linear, polynomial, and exponential regressions.

2. Materials and Methods

2.1. AirFresh air quality monitoring station

The monitoring of CO concentration from the level of UV radiation was carried out using AirFresh air quality monitoring stations and a developed portable station for measuring the level of the UV index. The stations' sensors are located in an urban area. In particular, the location is characterized by heavy traffic nearby and the absence of large industrial sources, which makes it a typical example of an urban background observation post.

The AirFresh station is equipped with sensors for measuring gas impurities and meteorological parameters. In particular, data was collected at 20-minute intervals and automatically transmitted to the EcoCity server. The UV index level was measured by a portable station and aggregated in a local database. The analysis was conducted on a sample of data collected over several days, in particular, from March 17 to March 21, 2025. Anomalous measurements (bursts of sensor noise) and time intervals with incomplete data were previously removed from the data.



a) b)

Figure 1: AirFresh air quality monitoring station installed on the territory of the TNTU building (a) and portable station for measuring the level of UV index (b).

3. Results and discussion

The correct choice of input parameters is crucial for predicting pollutant concentrations. In particular, Figure 2 shows heat maps demonstrating the change in the UV Index and carbon monoxide concentration in the atmosphere during the period from March 17 to March 21, 2025.

The left side of the figure shows the UV Index heatmap, while the right side shows the CO heatmap. The color scale on the left shows the intensity of the UV Index, where darker blue tones correspond to higher values, namely up to 5.0, while light yellow tones are close to zero. On the right heatmap, the color scale indicates the CO concentration, i.e., red tones are high (up to 1.4 mg/m³), while light yellow tones are low (about 0.7 mg/m³).

The analysis of heat maps shows a clear trend, i.e., during periods of high UV Index (during the day), a decrease in CO levels is observed. For example, on March 18, from 12:00 to 16:00, when the UV Index was 4.7-4.8, the CO concentration decreased to 0.7-0.8 mg/m³. At night, when the UV Index is zero, the CO concentration remains consistently high (1.2-1.4 mg/m³). This confirms the inverse relationship between the intensity of ultraviolet radiation and the level of carbon monoxide in the air.

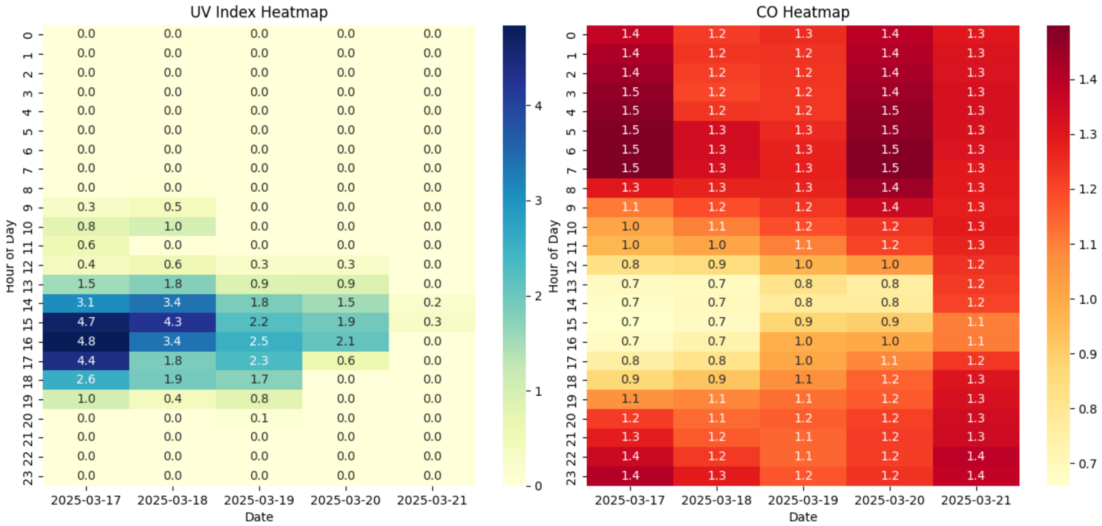


Figure 2: Daily measurements of UV Index and carbon monoxide CO concentration.

The temporal dynamics of the UV Index and CO concentration in the time range from March 17 to March 21, 2025 is shown in Figure 3. The graph shows that the maximum values of the UV Index are observed in the afternoon, while the CO concentration has the opposite dynamics: it decreases during periods of maximum solar irradiation.

The graph indicates the photochemical effect of CO decay, i.e., under the influence of solar ultraviolet radiation, carbon monoxide is oxidized, which leads to a decrease in its level in the atmosphere. After sunset, the intensity of the UV Index decreases to zero, which is accompanied by an increase in CO levels due to the absence of photochemical processes.

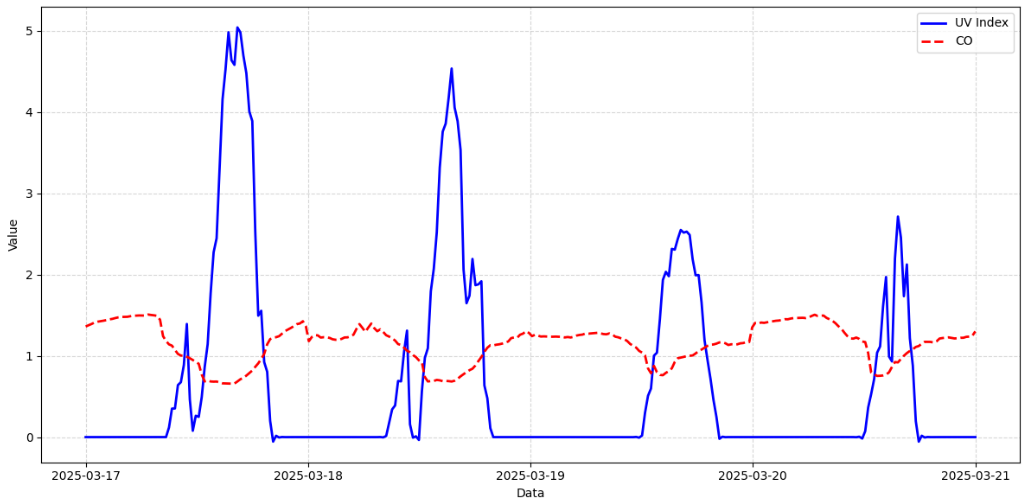


Figure 3: Temporal dynamics of UV Index and CO concentration changes in the time range from March 17 to March 21, 2025.

Thus, the identified relationship between ultraviolet radiation intensity and carbon monoxide concentration indicates the need to use modern approaches to model this relationship. Since traditional statistical methods often do not take into account complex nonlinear effects, it is advisable to use machine learning methods that allow for more accurate predictive models.

The process of developing a machine learning model involves several successive stages, each of which is critical to ensure its efficiency and accuracy. Each stage has its own importance and affects the final quality of the model. In general, the development of a machine learning model covers the following key stages: data collection, data preprocessing and analysis, selection of a model and machine learning algorithm, data separation into training and test samples, model training, evaluation and validation [22,23]. In the context of environmental monitoring, special attention is paid to tracking CO concentrations, which is one of the main pollutants Predicting CO concentrations is an important step in controlling air pollution and making management decisions.

The dataset contained 360 elements. To build and validate the models, the original sample was divided into two subsets, namely the training (80% of all data) and the test (20%). The distribution was performed randomly, ensuring that different UV ranges were evenly represented in the test subset. An artificial neural network (MLP) was chosen as the main prediction method. The network architecture consists of the following layers: input, hidden, and output. The input was two values, that is, the current UV and time, and the output of the network was the predicted CO concentration. In particular, the neural network model consists of four hidden layers containing 500, 300, 200, and 100 neurons, respectively. The ReLU function is used for activation, which ensures fast training and efficient processing of nonlinear dependencies. The model output uses a linear activation function suitable for regression tasks. The network is trained using the Adam optimizer with a regularization parameter $\alpha = 0.0001$ and an initial training rate of 0.001. Training continues until convergence is reached or the maximum number of iterations is reached, namely 5000, using an early stopping mechanism to prevent overtraining. Random initialization of the weights is performed using a fixed parameter random_state equal to 42 to ensure reproducibility of the results. Theoretical studies on recurrent neural networks with discrete delays have demonstrated that Lyapunov-based methods can provide exponential decay estimates, ensuring stable and predictable model dynamics during training [24]. In addition to the neural network, three regression models were built for comparison: linear, fourth-order polynomial, and exponential. The parameters of these models were estimated using the least squares method on the training sample. It was found that the built models can make predictions based on data that were not used in the training sample. Therefore, such results are informative for studying their quality.

Figure 4 shows a comparison of CO concentration prediction models depending on the UV Index.

The MLP model (R^2=0.80) provided the best fit to the data due to the neural network's ability to capture nonlinear dependencies. While linear regression showed the lowest accuracy (R^2=0.60), which is explained by the model's limited ability to describe the dependency curve. The polynomial model (R^2=0.72) captured the curvature well, but is partially prone to overfitting. The exponential model (R^2=0.64) confirms the nonlinearity of the relationship, but has limited accuracy due to the simplified form of the function.

In general, the results demonstrate a statistically confirmed inverse relationship between the UV Index and CO concentration in the atmosphere. This is consistent with the physical process of photochemical decomposition of CO under the influence of solar radiation. The application of the MLP neural network allowed us to obtain the most adequate model that explains 80% of the variation of CO with the change in the UV Index. Whereas traditional regression models proved to be less effective, since they do not take into account the complex nonlinear processes inherent in atmospheric phenomena. Thus, the proposed approach serves as the basis for predicting CO levels in urban areas at different intensities of solar irradiation.

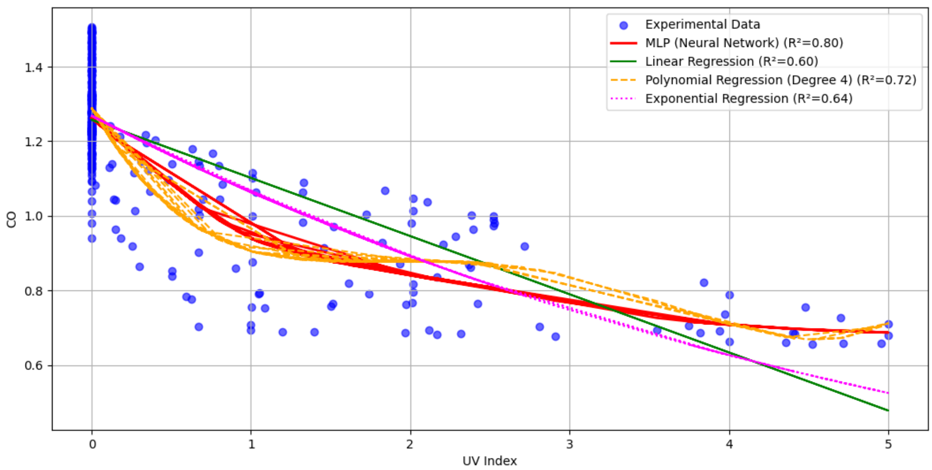


Figure 4: Predicted and experimental dependences of CO concentration on UV index during March 17-21, 2025 in the test sample.

Table 1 shows the results of predicting CO levels based on the UV Index for four models: neural network (MLP), linear regression, fourth-degree polynomial regression, and exponential regression. In general, the coefficient of determination R^2 shows how well the model explains the variation of the dependent variable, while MSE shows the average error between the prediction and actual values, and MAPE shows the average relative error in percent.

Table 1
Results of CO level prediction based on UV Index for different models

Model	R^2	MSE	MAPE
MLP	0.800000	0.014669	8.581848
Linear Regression	0.603735	0.019380	10.115384
Polynomial Regression	0.723149	0.013540	8.588277
Exponential Regression	0.644381	0.017392	9.655235

MLP is the most effective model in terms of prediction accuracy and consistency with real data. Due to its ability to handle complex nonlinear dependencies, the neural network provided the best R^2 value. In particular, the small value of MAPE indicates the model's high resistance to abnormal values. While the linear regression demonstrates the worst result due to its simple linear form, which does not take into account the nonlinear relationship between UV Index and CO. This model is not suitable for tasks where data have complex dependencies. Polynomial regression performed well due to its ability to describe curvilinear relationships. However, its main disadvantage is the tendency to overfitting, especially if you expand the range of UV Index values beyond the training set. The exponential model partially reflects the nonlinearity of the relationship between UV Index and CO, but its structure does not allow for accurate modeling of more complex patterns. This model is acceptable only for approximate estimation.

In general, the best accuracy was achieved by the MLP model when only one factor (UV Index) was taken into account. The value of R^2 = 0.80, although quite high, means that about 20% of the variation in CO concentration is not explained by changes in the UV Index. Therefore, to further improve the quality of the prediction, we will expand the set of input data. In particular, integration of other parameters that affect CO concentration is a promising direction. For example, these are indicators related to emissions from transport and industry, namely, suspended particles (PM_2.5, PM_10), nitrogen dioxide (NO_2), ammonia (NH_3) and other substances measured by the AirFresh network. Taking these impurities into account as additional inputs can provide the model with information about the intensity of pollution sources in different periods. Additionally, important meteorological parameters are temperature, humidity, wind speed, and the presence of inversions, which determine the dispersion and accumulation of CO. Enriching the model with such data and methods is the subject of further research. The results obtained and future research in this direction are related to the studies presented in [25-28].

Conclusions

This paper demonstrates that the neural network effectively predicts the CO concentration in the air based on the UV index. The resulting model provided a high coefficient of determination equal to 0.80, which significantly outperforms the accuracy of traditional linear and nonlinear regression approaches, such as linear regression, fourth-degree polynomial regression, and exponential regression. This demonstrates the high adaptability of machine learning algorithms to environmental monitoring tasks, especially in cases where the relationships between variables are complex and nonlinear. Comparison of the models showed that the MLP method has not only the highest coefficient of determination (R^2), but also a lower mean square error (MSE) and mean absolute percentage error (MAPE), which indicates the stability and accuracy of the prediction in the face of variable atmospheric factors. In particular, the MLP model provided a more accurate prediction compared to the fourth-degree polynomial regression, which, although it performed well, had a larger error due to possible overfitting. The linear and exponential regressions failed to adequately account for the nonlinear relationship between UV Index and CO concentration, which led to a decrease in their accuracy.

The analysis of the relationship between UV and CO showed that an increase in solar radiation intensity leads to a decrease in CO concentration in the atmosphere. This phenomenon is interpreted as a consequence of photochemical oxidation of CO. Thus, the UV factor can be used as an indirect predictor to estimate CO fluctuations throughout the day, which is especially important for urban environments with high traffic activity.

The results confirm that the application of neural networks to environmental monitoring tasks has significant potential. This is especially true in urban environments, where the level of air pollution depends significantly on meteorological parameters and anthropogenic factors. A promising area for further research is the development of comprehensive models that take into account not only the UV Index but also other meteorological indicators, such as temperature, humidity, and wind speed, to more accurately predict the concentrations of CO and other pollutants. This will improve early warning systems for rising air pollution levels and contribute to more effective air quality management in urban agglomerations. Recent applications of regression modeling with ROC analysis in medical prediction tasks demonstrate the value of statistical validation in forecasting systems, suggesting that similar diagnostic tools could enhance the reliability of air pollution alerts [29-32].

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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