



## CO Emissions Modeling and Prediction using ANN and GIS

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### ABSTRACT

Air pollution is considered a global concern due to its impacts on human life and the urban environment. Therefore, precise modeling techniques are necessary to predict air quality in congested areas such as megacities. Recently, machine learning algorithms such as Neural Networks show significant possibilities in air quality studies. This paper proposes a model to estimate air quality in a congested urban area in Baghdad city using Artificial Neural Network (ANN) algorithm and Geospatial Information System (GIS) techniques. Carbon Monoxide (CO) gas is selected as the main air pollutant. The model parameters involve; CO samples, traffic flow, weather data, and land use information collected in the field. The proposed model is implemented in Matlab environment and the results are processed after entering ArcGIS software. Using its spatial analysis tools, the outputs are presented as a map. The final findings indicate the highest value of CO emissions that reached 34 ppm during the daytime. The most polluted areas are located near congested roads and industrial locations in comparison with residential areas. The proposed model is validated by using actual values that are collected from the field, where the model's accuracy is 79%. The proposed model showed feasibility and applicability in a congested urban area due to the integration between the machine learning algorithm and GIS modeling. Therefore, the proposed model in this research can be used as a supportive model for decision making of city managers.

**KEYWORDS:** Air pollution maps, CO emissions, ANN, GIS.

### INTRODUCTION

The urban environment with different facilities such as roads network, industrial and commercial facilities, has a significant impact on the development of countries' economies (Guzman et al. 2016). In other words, due to the emission of pollutants from traffic, industrial and construction activities, air quality in urban areas is lower than in rural areas. Many pollutants are located in the ambient air such as Carbon Dioxide (CO<sub>2</sub>), Nitrogen dioxide (NO<sub>2</sub>), Sulfur dioxide (SO<sub>2</sub>), and Carbon Monoxide (CO). CO is the most poisonous gas, which mainly resulted from the incomplete combustion of fuels in the traffic emissions (Atimtay et al. 2000). It is a toxic, odorless, and colorless gas (Prockop and Chichkova 2007). As a result, many agencies and governments need the measuring and evaluating tools to model and assess the air pollutants and their impacts on the air quality to prepare valid plans to reduce air pollutants. Several methods are applied for air pollution assessment, which are categorized from direct measurement, mathematical simulations, prediction models, and spatial simulations (Sportisse, 2007). Although these methods make satisfactory results, there

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are still drawbacks to their performance. Direct measurements are an extremely expensive method and the mathematical simulation is unable to connect results with real locations. Machine learning algorithms such as Artificial Neural Network (ANN) algorithms show feasibility in air pollution studies due to their accurate results and their compatibility with other techniques such as spatial models (Jiang et al. 2004). In several recent studies, studies on modeling and evaluating air quality in the city and busy areas of Tehran and Baghdad, the use of neural networks has been suggested. In one of them, Farhadi et al. (2019) showed that the use of artificial neural networks with inappropriate inputs is not efficient for modeling PM<sub>10</sub>. However, the results of Azeez et al. (2019) that study in Iraq, showed that an accuracy of about 80% can be achieved. Then Jasim et al. (2020) resulted that the integration between air pollution models and Geospatial Information System (GIS) techniques could be a useful tool for urban air quality assessment and urban planning. In this study, we propose a hybrid model which integrates the ANN algorithm and GIS techniques (spatial analysis) to produce CO maps and prediction model in the study area.

In general, several methods have been utilized to predict air pollutants in urban and rural areas such as the following; (1) Direct measurements such as field surveying, (2) Mathematical simulations, (3) Prediction models, and (4) Spatial models such as dispersion and GIS models. Recently, hybrid models that integrate artificial intelligence algorithms and spatial techniques showed good feasibility in the air quality modeling as well as their high performance in the spatial representation of air pollutants at a certain time and location (Azeez et al., 2019). Traditional interpolation is considered the basic technique used in the spatial modeling of air quality. Potoglou and Kanaroglou (2005) proposed a method by integrating field data and the kriging interpolation method to represent the spatial variation of CO emissions. It was concluded that traffic areas were the most polluted locations in urban areas. In a separate study, Arain et al. (2007) developed a model using land use regression algorithm (LUR) and data obtained from the governmental sector such as traffic flow, weather data, and land use maps. That study aimed to estimate Nitrogen dioxide (NO<sub>2</sub>) emissions in Canada. The final findings showed a significant spatial pattern of NO<sub>2</sub> at the local scale. After that, the experts developed a special model to estimate the dispersion of air pollutants; (Kho et al. 2007). They predicted CO emissions within a congested area in Malaysia by dispersion software (CAL3QHC), which uses traffic flow data and weather information. They concluded that CO values on roads were highest than CO values near residential areas. In another study, Behera et al. (2015) proposed a new framework using data obtained from monitoring stations and GIS techniques to generate prediction maps of NO<sub>2</sub> concentrations in India. The results of that study showed high concentrations of NO<sub>2</sub> in the center of the city near commercial facilities. Due to the increase of the governmental data, Kim and Guldmann (2015) developed a LUR model depending on monitoring stations and a new proposed parameter vehicle-kilometers-traveled to estimate NO<sub>2</sub> values in Seoul, South Korea. As a result of that research, it was found that Land use and vehicle-kilometers-traveled had a significant impact on the NO<sub>2</sub> levels. Recently, Machine learning methods become the most popular methods for air quality modeling, due to their ability to overcome complicated computation issues and optimize modeling performance. For instance; Moazami et al. (2016) developed a prediction model using a support vector machine algorithm to predict daily CO concentrations with a small dataset. Most recent studies aimed to model and represent air pollutants at a micro-scale by using machine learning methods and GIS tools. Azeez et al. (2018) developed an integrated model based on the Support Vector Regression Model and GIS spatial analysis with grid analysis to produce prediction maps on near highways in Kuala

Lumpur, Malaysia. The final findings indicated that the highest CO levels were observed during daily peak hours.

The main drawback of interpolation results is that the results lack reasoning due to their negligence of barriers like buildings and the topography which may affect the interpolation process. On the other hand, dispersion models required extensive information, the mismatching between data. While the main drawback of Land use regression models are the area specificity, the robustness of the model depends on the area of study. Finally, machine learning algorithms required Big data and expert users (Zhou et al., 2017). Thus, in this study, we tried to solve these problems by combining ANN algorithm and GIS tools to model CO emissions in urban areas in the center of Baghdad, Iraq.

## MATERIALS AND METHOD

The study area is selected in a small urban area located in Baghdad city called "Al karkh". The main reason for selecting this area is the availability of air quality data. Al-karkh is generally a congested area in Baghdad city. The two sides of Baghdad city (Karkh and Resafa) are connected through an important road network. On the other hand, this area contains several land-use types (Figure 1). The center of Baghdad is geographically bounded by (33° 20' 0" N, 44°23'30" E) and (33° 20' 30" N, 44° 22'30" E). In Baghdad, the weather is hot-dry in summer and mild in winter. Baghdad is characterized by a flat topography. According to governmental statistics, the population in Baghdad reached approximately 7 million (Iraq National Population Commission, 2012). This area is called (Old Alkarkh) due to the variation of activities including commercial, industrial, transportation, and residential ones. This area is also unique by the heavy traffic congestions during rush hours that can daily influence the quality of ambient air. Furthermore, this area also includes many heritage buildings which makes it suitable for tourism activities and environmental studies.

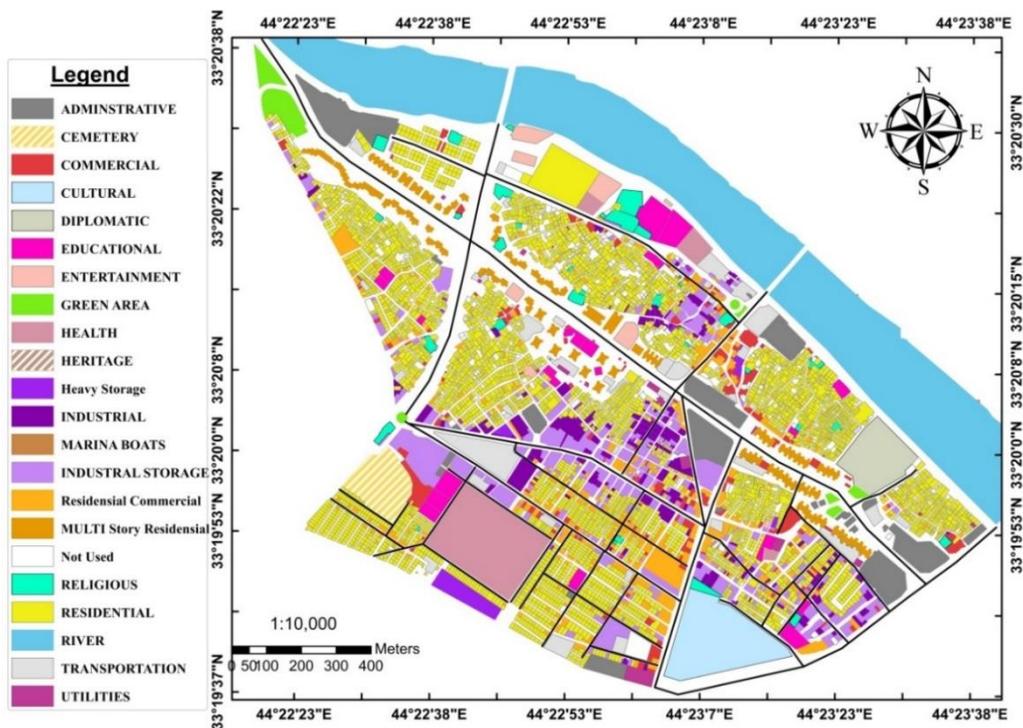


Fig. 1. The Study area (Alkarkh area)

The proposed methodology includes several steps; the first step is the field data collection including a number of light vehicles, heavy vehicles, motorbikes, temperature, humidity, wind speed, wind direction, and CO emissions, then the collected data are converted to excel files to facilitate the integration with the modeling process. The modeling process is applied depending on the input parameters (a number of light vehicles, heavy vehicles, motorbikes, temperature, humidity, wind speed, wind direction, land use, proximity to roads ) and the ANN algorithm. After that spatial modeling is applied depending on ANN results and spatial analysis techniques (i.e. IDW interpolation, conversion analysis) to produce CO emission maps in the study area. Figure 2 shows the overall methodology.

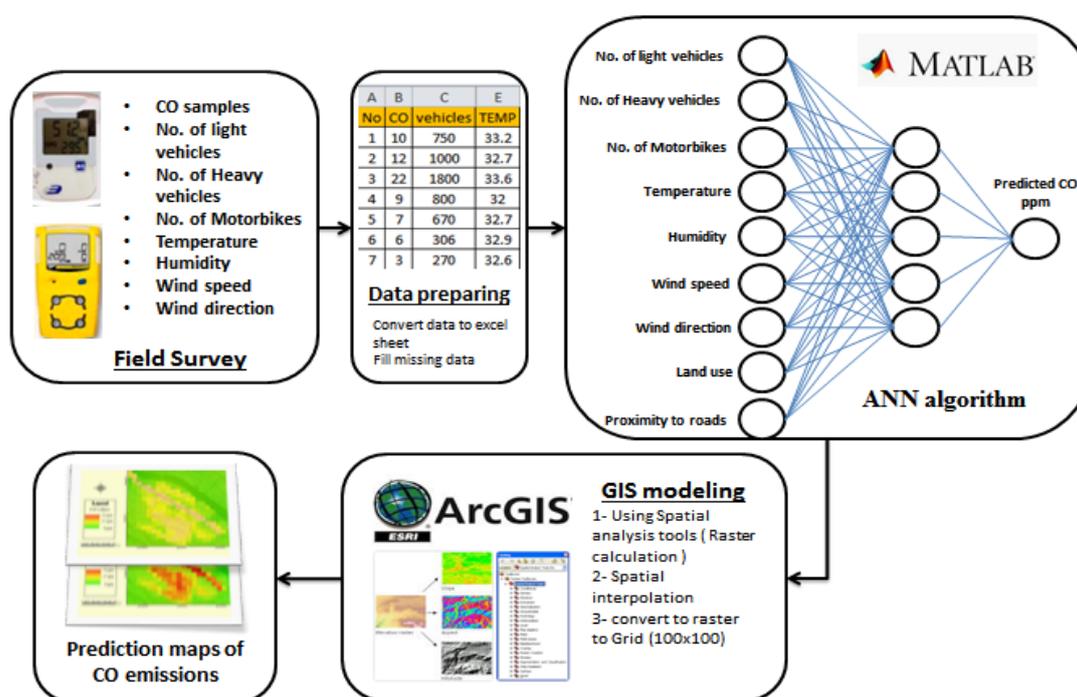


Fig. 2. Proposed method

The field survey was conducted by the Iraqi Ministry of Environment and continued for one month, the survey had contained the collection of CO emissions at certain times and locations. CO emissions were frequently measured by using mobile equipment. On the other hand, traffic flow and weather data were simultaneously recorded with CO emissions. Sample locations were randomly selected depending on spatial analysis techniques, which created an optimal number of samples in the study area (Ragetti et al. 2016). The data were gathered in April 2019 by a group of surveyors. These data included CO samples that were collected using portable equipment, model CO tracker with an accuracy of one part per million (ppm). The traffic flow and weather data were collected simultaneously per hour. Where the traffic flow information included a number of light vehicles, heavy vehicles, and motorbikes, which counted manually. On the other hand, weather data including temperature, humidity, wind speed, and wind direction were collected by using a data logger. The measurements were conducted twice per day; daytime (6.30 am to 3.30 pm) and nighttime (5 pm to 12 pm) according to the instructions of World Health Organization (WHO) (2006). The field survey results showed that the average temperature, humidity, the wind speed were equal to 34°, 43%, 7.3 mph, respectively. In addition, the wind direction was 41 North. In terms of the number of vehicles, light and heavy vehicles were equal to 2600 and 740. The number of motorbikes was 87.

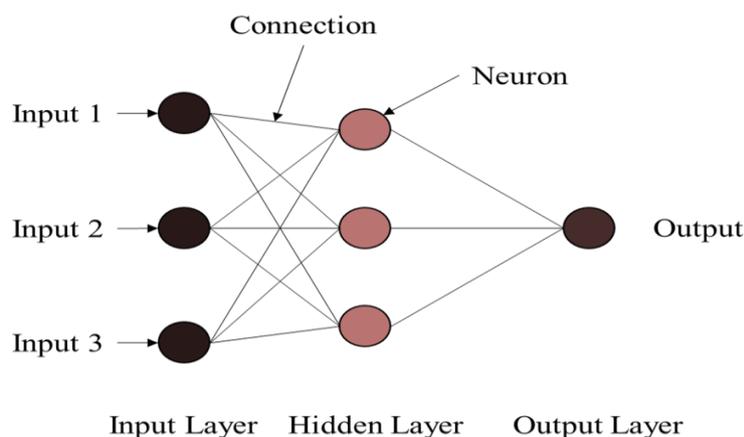
ANN is one of the biological mathematical learning algorithms that belong to machine learning models. As it is shown in Figure 3, ANN consists of a simple framework that connects nodes and neurons. The ANN algorithm can represent a non-linear mapping among inputs and outputs. Neurons are organized into several layers with random or full connections between successive layers (Mokhtarzade and Zoej, 2007). Generally, in the ANN architecture, there are three types of layers which are input layer, hidden layers, and output layer. These layers are responsible for processing the input data and present final outputs (Mokhtarzadeh and Zoej, 2007). While, nodes are connected by numerical weights and output signals that considered as a function of the sum of the inputs to the node modified by an activation function (Gardner and Dorling 1998). Back-Propagation (BP) algorithm is a famous algorithm for ANN. Furthermore, the BP algorithm is considered an iterative algorithm that is developed to decrease function errors (Eq. 1).

$$E = \frac{1}{2} \sum_{i=1}^L (d_j - o_j^M)^2 \quad (1)$$

where,  $d_j$  and  $o_j^M$  refers to desired outputs, current response of the node  $j$  in the output layer, and  $L$  refers to the number of nodes within output layer. In an iterative method, the correction of weight parameters is calculated as (Eq. 2).

$$\begin{cases} \Delta w_{i,j} = -\mu \frac{\partial E}{\partial w_{i,j}} \\ w_{i,j}(t+1) = w_{i,j} + \alpha \Delta w_{i,j}(t) \end{cases} \quad (2)$$

where,  $w_{i,j}$  refers to the weight parameter between node  $i$  and  $j$ ,  $\Delta$  a positive constant, which controls the amount of adjustment and  $\alpha$  is named as learning rate and also  $\mu$  is a momentum factor that can classified between 0 and 1. The parameter  $t$  represents the iteration number. In the other word, the parameter  $\alpha$  can be named as stabilizing or smoothing factor as it smoothest the fast changes between weights (Yang 1995). Figure 3 shows a simple example of the structure of a neural network.



**Fig. 3.** ANN structure (Ahmed and Pradhan 2019)

In this study, we applied a backpropagation algorithm with an architecture that included 9 input layers with 5 neurons for each layer by using MATLAB software. The input layers include several parameters like the number of light vehicles, heavy vehicles, motorbikes, temperature, humidity, wind speed, wind direction, land use, and proximity to roads. The

modeling process is implemented depending on collected samples, the total number of samples is 88, the modeling samples were 62 which represents 70% of the total number of samples, while the validation samples were 26 represent 30% of total samples. The model's validation is implemented by using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient methods.

In this study, GIS modeling is implemented depending on spatial analysis techniques by using ArcGIS software. The main goal of using GIS modeling in the study is to produce maps that represent the spatial and quantitative variation of CO emissions in the study area. GIS modeling typically includes several steps, the first step is data transformation from the vector to the raster format. The main reason for the data transformation is to facilitate the integration between spatial analysis tools and the input data due to the applicability of raster layers in the GIS environment. In this regard, spatial interpolation is applied by using the Kriging algorithm. Kriging is a geostatistical interpolation that generates a predicted surface from a distributed set of points with a specific value. The kriging interpolation assumes that distances or directions between sample points reflect a spatial correlation that can be used to explain variation in the values. The kriging interpolation process includes several exploratory statistical calculations, generating the surface, variogram modeling, and exploring the variance of surfaces (Dai et al. 2003). Furthermore, the proximity to roads parameter is calculated by using the Euclidean distance tool. The final result shows the spatial distribution and quantitative variation of CO emissions with cell-size (100 × 100) m.

## RESULTS AND DISCUSSION

The proposed model (ANN) is tested and validated depending on 9 parameters; ( the number of light vehicles, heavy vehicles, and motorbikes, Temperature, Humidity, Wind speed, wind direction, land-use, and proximity to roads) to model CO emissions. According to the result of modeling, the accuracy of ANN algorithm achieved 79%, the correlation coefficient is 0.9734, Mean absolute error is 1.3172 and Root mean square error is 2.156. Table 1 shows the accuracy assessment of CO prediction based on ANN algorithm.

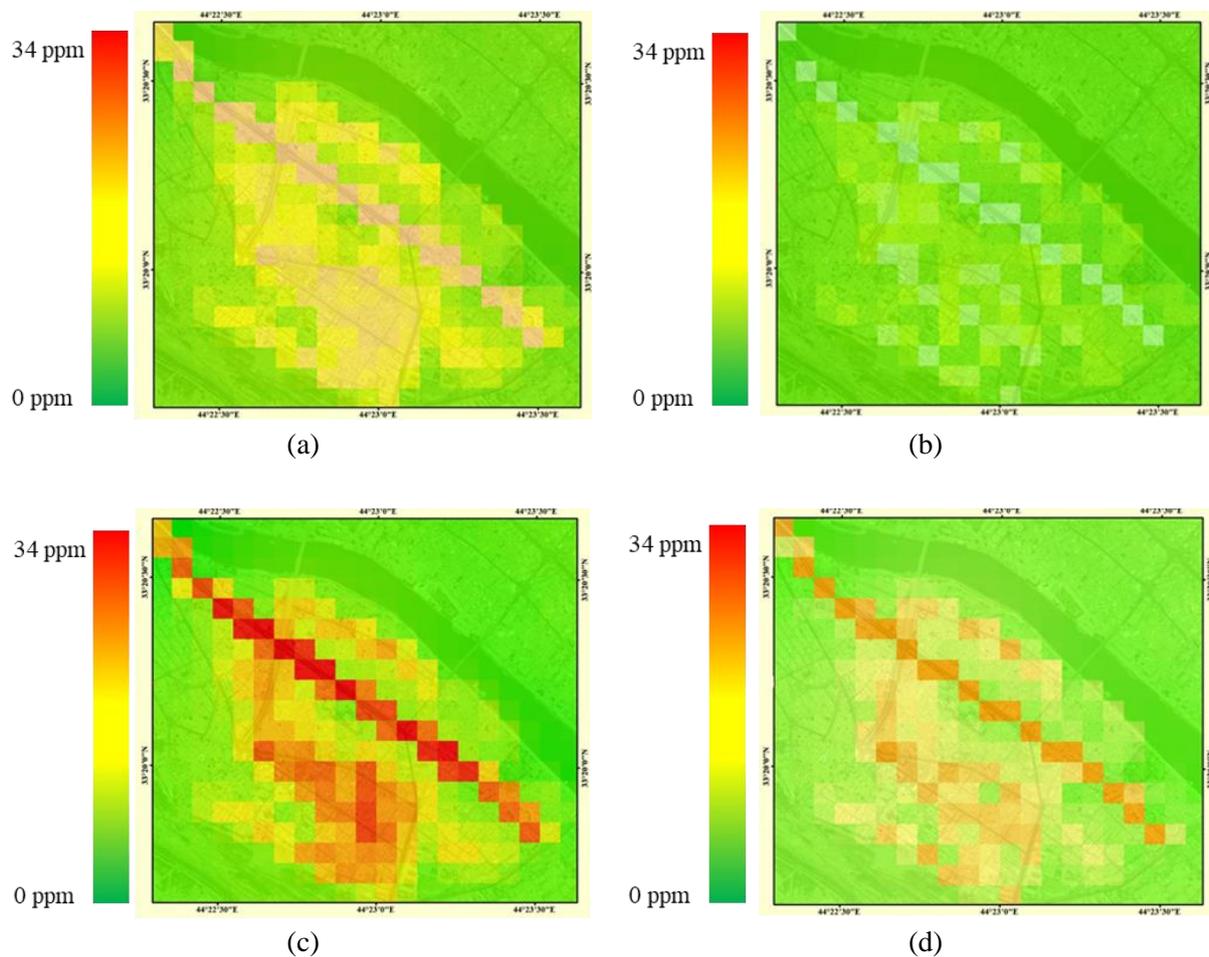
**Table 1.** The accuracy assessment results depending on ANN algorithm

<b>correlation coefficient</b>	<b>0.9776</b>
<b>MEA</b>	1.321
<b>RMSE</b>	2.023
accuracy	79 %
number of parameters	9

The result of GIS modeling is presented depending on the prediction maps. According to these maps, the highest levels of CO are detected through the daytime because of the heavy traffic jam and traffic activities including industrial, and commercial activities. In contrast, the lowest values of CO emissions are detected during nighttime due to the decrease of traffic activities and other manmade activities. Workdays have recorded the highest value of CO emission reached 34 ppm through daytime compared to their values at nighttime that reached 19 ppm. On the other hand, holidays recorded the lowest values of CO emissions 9 ppm at nighttime while CO emissions reached 12 ppm in the daytime. According to the spatial variation of the CO emissions, we find that the highest values are concentrated near road network, industrial locations and commercial areas due to the traffic congestions, exhausts of small generators that used in industrial workshops and commercial areas. In contrast, the lowest values located far from roads, near residential and green areas. Therefore, traffic

activities, industrial, and commercial locations showed a high correlation with CO emissions within the study area.

The first map is showing the CO values at Holiday during the daytime, where the emissions are relatively low, where the CO values ranged from 0 ppm to nearly 19 ppm, the highest values were concentrated on roads because of the traffic flow. Contrary, the second map is representing CO values at Holiday during nighttime, where the CO values decreased due to the decrease of traffic activities, the CO values were between 0 ppm and 14 ppm. Figure 4 (a), (b)). On the other hand, the third map is presenting the CO values at Work-day during the daytime, CO values have significantly increased, CO values ranged from 0 ppm to 34 ppm, the highest CO values concentrated near roads and industrial workshops. While some residential areas located near workshops and main roads are affected by CO emissions, which reached 28 ppm near these areas. The fourth map is showing a slight decrease in the CO values during nighttime at work-day, due to the normal decrease of traffic activities in this area. Figure 4 (c), (d)). According to maps, we concluded that the study area is subjected to air pollution during workdays more than holidays.



**Fig. 4.** CO emissions at holiday –Daytime (a), holiday –Nighttime (b), Workday –Daytime (c) and Workday –Nighttime (d)

In general, by comparing CO emissions recorded per 1 hour, the highest values of CO emissions have exceeded the standards that adopted WHO and United States Environmental Protection Agency (USEPA), where the highest value of CO should not be increased by 26

ppm (WHO) and 35 ppm (USEPA standards). As a result, the people living near roads or industrial areas are daily exposed to several harmful emissions that may affect their health. Therefore, a proper strategy should be applied to reduce air pollution in this area.

## CONCLUSION

CO emissions are one of the main air pollutants in urban areas. The modeling and mapping techniques are usually applied to assess the impacts of air pollution on the environment and human health. In this study, we propose a model which is based on ANN and GIS tools to model CO emissions in a small urban area. The proposed methodology is trained depending on 9 parameters, ANN model accuracy is 79%. The spatial modeling is applied depending on spatial analysis techniques and the Kriging interpolation algorithm to represent the distribution of CO emissions at different times a day. The highest value of CO emissions which is 34 ppm, is found near roads. On the other hand, the lowest value of CO emissions which is 0 ppm is found near residential areas. Road networks, industrial, and commercial land use have shown significant impacts on CO emissions while residential land use shows the lowest impacts with CO emissions. The proposed model shows the feasibility and applicability in a congested urban area. As the conclusion, the proposed model in this research can be used as a supportive model for decision making of city managers.

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## CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

## LIFE SCIENCE REPORTING

No life science threat was practiced in this research

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