



Assessing and predicting air quality in northern Jordan during the lockdown due to the COVID-19 virus pandemic using artificial neural network

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Abstract

This study deals with the simulation and prediction of air pollutants in Irbid city (north of Jordan) before and during the spread of the COVID-19 virus pandemic by using an artificial neural network (ANN). Based on the data obtained from the air quality monitoring station for the year 2019 and the first quarter of the year 2020, it was possible to develop an ANN model to simulate and predict the concentrations of three air pollutants, namely nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and particulate matter with diameter less than 10 μm (PM₁₀). Several ANN model configurations were tested to select the best model that could predict the concentration of the three air pollutants with meteorological parameters being used as input to the model. The results showed that the concentration of the pollutants during the coronavirus lockdown was declined by various percentages (from 29% for PM₁₀ to 72% for NO₂) as compared to their concentration before the pandemic period. Furthermore, the developed ANN model could simulate and predict the concentration of the pollutants during the pandemic period with sufficient accuracy as judged by the values of the coefficient of determination and the mean square error. The study results indicate that properly trained and structured ANN can be a useful tool to predict air quality parameters with adequate accuracy.

Keywords Coronavirus pandemic · Lockdown · Air pollution · Artificial neural network · Northern Jordan

Introduction

Since reporting of the first infected case by a coronavirus in Wuhan (China), the disease has been spreading worldwide and reached a pandemic level as announced by the World Health Organization (WHO). The pandemic has adversely affected many aspects of our daily life (Khan et al., 2020), where, as of November 8, 2020, 50.10 million are infected persons with total death cases of 1,253,110 (JHU, 2020). In order to prevent the transmission of the pandemic to their territories, most of the countries worldwide put travel restrictions and border control and closure and have been isolated

from the rest of the world (Wells et al., 2020). In addition to isolation, to prevent the spread of the coronavirus within the country and to minimize the infections, several countries had a complete shutdown that reached the level of curfew, where vehicles' and individuals' mobility was prohibited.

Some studies were carried out during the first quarter of 2020 to report on the relationship between the lockdown that took place in countries in order to prevent the spread of the pandemic and the quality of the air in those areas. It can be noticed that most of the researchers reported improvement in the air quality parameters like carbon and nitrogen dioxide emissions (Isaifan, 2020; Dutheil et al., 2020). On the other hand, Wang et al. (2020) reported deterioration of air quality in some cities in terms of PM_{2.5} concentrations, which was mainly due to meteorological conditions during the study period.

There is a mutual interaction between air quality and the number of mortalities resulted from the spread of coronavirus. On the one hand, the presence of coronavirus in poor air quality areas can lead to increased morbidities and mortalities, especially in countries that did not enforce the lockdown immediately after the spread of the pandemic like Italy (Conticini et al., 2020). For example, Ogen (2020) indicated that the

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long-term exposure to nitrogen dioxide could contribute to increased fatality caused by the COVID-19 virus in regions where the nitrogen dioxide concentration is high. On the other hand, lockdown soon after the spread of coronavirus pandemic as evidenced from several countries has led to a decline in the amounts of the emitted air pollutants and consequently improved air quality (Dantas et al., 2020; Abdullah et al., 2020; Isaifan, 2020; Dutheil et al., 2020).

Due to their fluctuating and its nonlinear nature, modeling of real-world processes such as air quality is generally a difficult task (Niska et al., 2004). Artificial neural network (ANN) modeling lends itself as a suitable method for simulating and predicting such a phenomenon. ANN is computing models that are trying to simulate a biological brain system through training and learning (Moustris et al. 2010). Typical ANN consists of three types of interconnected layers: the input layer through which the predictor data are fed into the model, while the second level layer is the hidden layer where the input data are subjected to processing by a suitable activation function and finally the output layer where the final output results are calculated. Within each layer, there are processing units called neurons. The number of layers at each level of ANN may vary from single to several layers (Baawain and Al-Serhi, 2014).

According to Cabaneros et al. (2019), research activity in the field of air pollution forecasting using artificial neural networks (ANNs) has increased dramatically in recent years for short- and long-term forecasts. Utilizing ANN modeling, it was possible to predict the particulate matter (PM₁₀) (Chaloulakou et al. 2003; Alam and McNabola, 2015), forecasting the concentration of particulate matter (PM_{2.5}) and carbon monoxide (CO) (Thomas and Jacko, 2012; Memarianfard et al., 2017), and nitrogen dioxide, ozone, sulfur dioxide, and PM_{2.5} (Ding et al., 2016). ANN has shown better predictability of air pollutants than other models like multiple linear regression and autoregressive integrated moving average (ARIMA) (Ding et al., 2016; Hosamane and Desai, 2018; Alimissis et al., 2018; Freeman et al., 2018).

The main objective of the present study is to assess and predict the impact of the lockdown as a result of coronavirus pandemic spreading on the air quality in northern Jordan using ANN based on two scenarios. The pollutants subjected to analysis were nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and PM₁₀, which are the main pollutants that are responsible for the degradation of ambient air quality, and cause several adverse impacts on the public health and environment (Hosamane and Desai, 2018).

Study area

The study area is located in northern Jordan, specifically, in the City of Irbid and its suburbs that has an area of 30 km² and located between 35° 49' 00" E to 35° 53' 00" E and 32° 31' 50" N to 32° 35' 00" N, respectively as shown in Fig. 1. The city

has an average elevation of 616 m above sea level and has moderate weather with an average annual air temperature of 23 °C and an average annual rainfall of 485 mm (JMD, 2016).

Irbid is the second-largest city in Jordan after the capital city of Amman. The city is the main urban center of Irbid Governorate, which is a crowded city with 5 universities and trade activities. The population of Irbid Governorate in 2017 was 1,911,600 as per the data from the department of statistics (DOS 2018), while the city and its suburbs accommodate 0.8 million (DOS, 2018). This number has been rapidly increasing as a result of the Syrian refugee influxes since 2011 (Abu Qdais and Shatnawi, 2019). Irbid has the highest population density in Jordan (1216.2/km²). The rapid population growth in Jordan together with the high rate of urbanization and the increase in the number of transportation vehicles have adversely affected the situation in the urban environment and resulted in increased levels of air pollutants (Shatnawi and Abu Qdais, 2019).

To respond to the challenge of coronavirus pandemic spread in Jordan, the Jordanian government followed a step-wise strategy. Implementing such a strategy started with preventing the flights from countries where the pandemic spreading rate was high (China, Italy, and Iran). After reporting the first infected case by a coronavirus in the country on March 15, 2020, the Jordanian government decided to close the borders, when no passengers were allowed to enter or leave the country. With the increase in the numbers of infected cases, the country adopted frequent partial and full lockdown measures, which reached the level of curfew on certain days and limited the inter- and intra-city mobility, where vehicles' and individuals' mobility was prohibited. Due to such strict and early measures, the number of the confirmed infected cases by COVID-19 in Jordan as of April 6, 2020, was 353; confirmed out of that, there were 138 recovery and 6 mortality cases. This is a relatively low number as compared to neighboring countries in the Middle East. This number included 95 infected cases in Irbid with one mortality (Abu-Qdais et al., 2020).

In Jordan, the Ministry of Environment is the main agency that is responsible for monitoring the air quality through real-time monitoring stations that are covering different areas in the governorates of Amman, Irbid, and Zarqa. In the city of Irbid, there are two monitoring stations, namely, Al-Baraha Street station, which is located nearby the city center and records the concentration of nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and particulates with less than 10 μm in diameter (PM₁₀). In addition, the Al-Baraha station records meteorological parameters like temperature, relative humidity, wind speed, and wind direction. The second station is Al-Hassan Sports city station which is located in the southern part of the city and records only nitrogen dioxide (NO₂), carbon monoxide (CO), and PM₁₀, with no records of meteorological parameters. Because of the availability of meteorological data

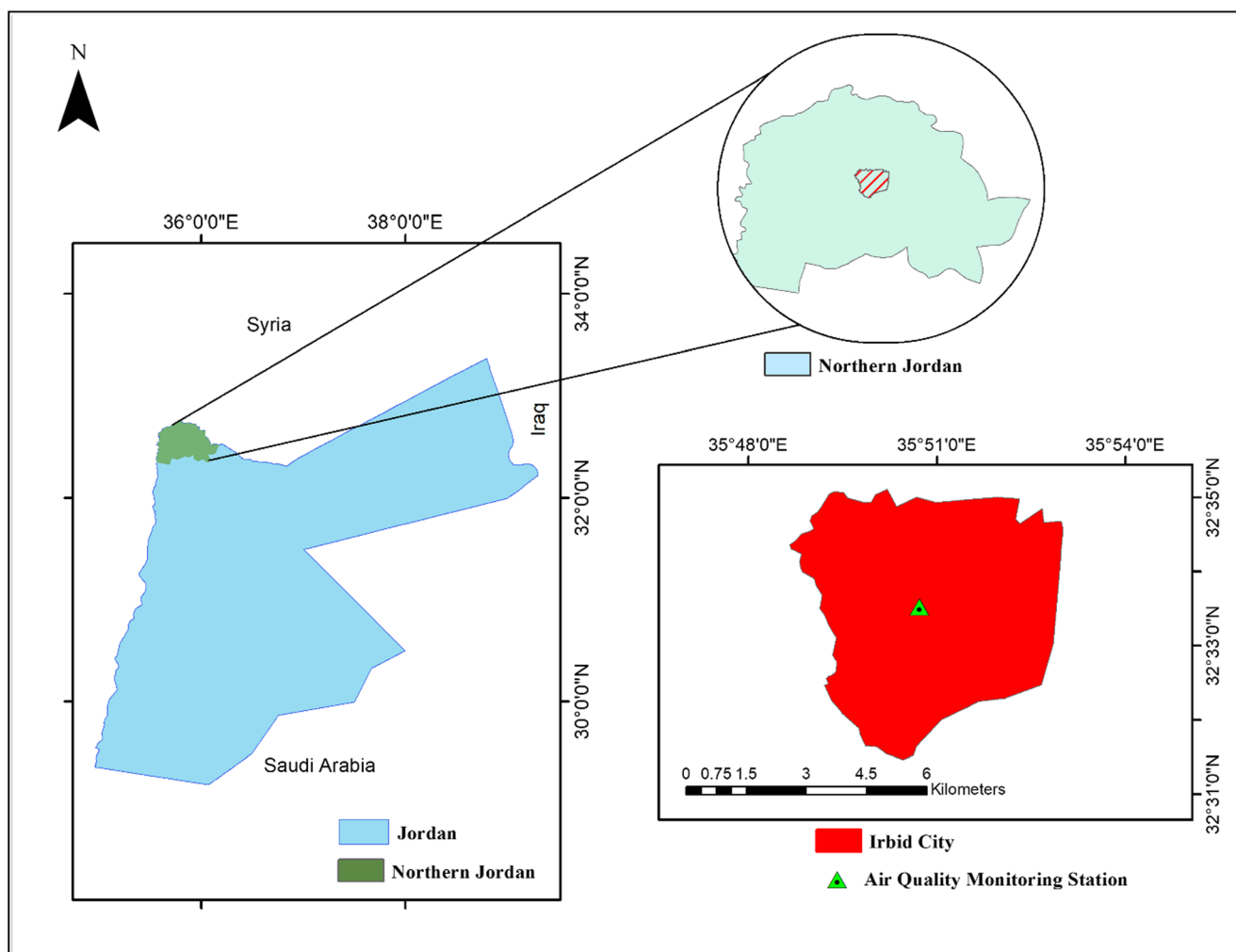


Fig. 1 Location map of the study area in the northern Jordan

from Al-Baraha Street station, and its location in the city center, it was decided to use the data from this station for the purpose of the study. Figure 1 shows the location of the station in Irbid city.

Study methodology

Daily average readings were obtained from Al-Baraha street station for two periods. The first period covers the full duration of the year 2019 (from January 1 until December 31, 2019). This period is considered as the pre-coronavirus pandemic period during which only 7 data points were missing, due to the availability of the station out of service. The second set of data covers the period from the beginning of the year 2020 until the date of writing up the current article (from January 1 until April 13, 2020) that represents the period during which the pandemic has been spreading and the Jordanian Government started adopting mitigation measures of lockdown and curfew.

Scenarios

To allow for assessing the impact of the coronavirus lockdown on the emitted pollutants, two scenarios were considered in ANN modeling as follows:

Scenario 1: Baseline scenario. Under this scenario, the daily meteorological data for the year 2019 (pre-pandemic period) that were obtained from the air monitoring station in Irbid was used as input data in developing the ANN model. After that, the developed model was used to predict the amounts of the emissions starting from January 1, 2020, based on the assumption as if the coronavirus pandemic did not take place.

Scenario 2: With pandemic scenario. To include the pandemic impact under the second scenario, in addition to the data of the year 2019, data until the middle of March 2020 were added to the ANN model input. The model predicted the emissions during the pandemic time from March 15 until the middle of April 2020, after

Table 1 Descriptive statistical analysis of the meteorological data set in the study area

Weather parameter	Number of data points (<i>N</i>)		Mean	Median	Std. deviation	Mode	Min	Max
	Scenario 1	Scenario 2						
Air humidity (%)	358	463	59.23	62.2	16.12	58.10	13.7	90.00
Ambient temperature (°C)	358	463	17.69	16.20	6.93	10.50	4.39	33.30
Magnetic wind direction (°)	358	463	159.10	145.00	56.53	117.0	70.80	280.40
Wind speed (km h ⁻¹)	358	463	4.71	4.17	1.947	3.07	2.12	14.40

which the predicted values were compared with the actual emissions data during the pandemic period.

Artificial neural network model

An artificial neural network was used to simulate and predict the pollutants' amount in the study area. In the present study, the ANN development process started with analyzing the collected data to select the input to the model. The data was subjected to preprocessing by calculating the statistical parameters, namely, mean, mode, median, and standard deviation. Tables 1 and 2 show the statistical parameters, for the measured meteorological and air quality parameters, respectively. Table 1 shows that the total data points used in developing ANN under scenarios 1 and 2 were 358 and 463, respectively.

It can be observed from Table 2 that the average measured daily concentration of the three studied pollutants are below the values of the allowed daily limits imposed by the Jordanian Ambient Air Quality Standard no. 1140/2006.

Exploratory factorial analysis (EFA) was used to construct validity of the data sample. The factors used were Kaiser-Meyer-Olkin (KMO) of sampling adequacy and Bartlett's test of sphericity. Tables 3 and 4 show the values of these factors which indicated that meteorological and air quality data met the sphericity and sampling adequacy assumptions. In other words, this confirms that the weather parameters were correlated and not orthogonal (Bal and Karakas, 2018).

For air pollution studies, the meteorological variables are used as predictors in the input layer of the ANN as they are influencing the dispersion and concentration of the air pollutants (Dominick et al., 2012; Kumar et al., 2017; Peng et al.,

2017). Therefore, in this study, ambient air temperature, humidity, temperature, wind speed, and wind direction were used as predictors. The data sets were divided into three groups for training, validation, and testing purposes, where 70% of the total data was devoted to model training (Chaloulakou et al., 2003; Alimissis et al., 2018) using the Levenberg-Marquardt training algorithm (Thomas and Jacko, 2012). The training aims to calibrate the connection weights between the various interconnected nodes of the model. Furthermore, 15% of the data sets were used for measuring the model performance through validation and the remaining 15% of the data sets were used to check the model robustness through model testing phase. Figure 2 presents a flowchart that depicts the methodology followed in conducting the study.

Results and discussion

Irbid has no major industries or airports. Therefore, vehicles' emissions are the major anthropogenic source of air pollution in the city. According to the Jordan Department of Statistics Report for the year 2018, the total number of licensed vehicles from all categories in Irbid Governorate is 116,399, out of which 33% uses diesel fuel, while the remaining uses gasoline. (DOS, 2018). To account for the seasonal impacts on the forecasted air pollutants, data covering 1 year were used in the model development. Analysis of the predicted air pollutants based on scenario II before and after the pandemic period reveals that the concentration of the air pollutants during the pandemic lockdown has been declined as compared with the concentration before the pandemic period. The decrease was found to be by

Table 2 Descriptive statistical analysis of the daily measured concentration of air pollutants in the study area

Pollutant concentration	Mean	Median	Std. Dev.	Mode	Min	Max	Allowable daily concentration by standard ¹
PM ₁₀ (µg/m ³)	39.74	34.00	23.27	34.75	6.14	236.00	140
NO ₂ (ppb)	12.01	11.32	5.26	8.19	1.50	29.35	80
SO ₂ (ppb)	7.036	5.55	3.96	4.73	1.47	24.90	140

¹ According to Jordan Ambient Air Standard No. 1140/2006

Table 3 Bartlett’s test of sphericity

Bartlett’s test of sphericity		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.807
Bartlett’s test of sphericity	Approx. chi-square	526.335
	df	6
	Sig.	0.000

72%, 52%, and 29% for NO₂, SO₂, and PM₁₀ respectively. A recent study conducted by the Jordan Ministry of Environment reported that during the pandemic lockdown period, there is a decrease of 75.8%, 60.2%, and 33.5% in the concentration of NO₂, SO₂, and PM₁₀ respectively as compared with the same period of the year 2019 (MOENV, 2020). Decreasing trends were found during the lockdown by other researchers in Brasil (Dantas et al., 2020), in Malaysia (Abdullah et al., 2020), in India (Sharma et al., 2020), and in many other countries of the world (Muhammad et al., 2020). However, up to the authors’ knowledge, none of the conducted studies adopted ANN to assess and predict the air quality parameters during the spread of coronavirus pandemic lockdown. In this study, the ANN model was developed using the MATLAB software by applying the backpropagation method to model and predict the daily average concentration of NO₂, SO₂, and PM₁₀ by feeding meteorological parameters as input to the model. The model structuring is an important step in the ANN model development process, where the number of layers and neurons at each level are identified. A general method that determines the optimal number of hidden layers and neurons does not exist (Cabaneros et al., 2019). In order to find the best structure of the network in this study, various network structures were evaluated. The accuracy of the training is affected by several parameters, such as training samples, training algorithm, and neuron activation function (Liu et al., 2008). A sigmoid activation function was used as it is the most popular function that describes nonlinear relationships. An ANN model with one hidden and sigmoid activation functions was able to simulate the data with good accuracy. The mathematical formula of the used activation function is given by Eq. (1):

$$S(x) = \frac{e^x}{1 + e^x} \tag{1}$$

where $S(x)$ is the activated value and x is the original value.

Table 4 Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

Weather parameter	Result
Humidity	0.878
Temperature	0.848
Wind direction	0.661
Wind speed	0.766
KMO	0.807

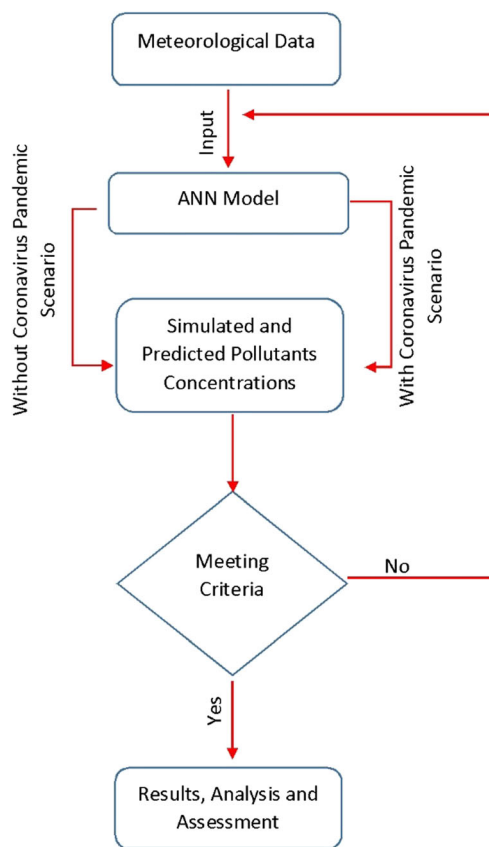


Fig. 2 Flowchart of the methodology followed in conducting the study

In this study, one input layer of 4 neurons was used with one output layer of 3 neurons. In order to determine the number of hidden layers and their neurons, a trial and error process was followed (Hosamane and Desai, 2018, Chaloulakou et al., 2012). Twelve trials (runs) were carried out to get the optimal number of neurons in the hidden layers (one hidden layer). The value of the root mean square error (RMSE) was consistently decreasing with each run until the run number 10 after which the values of RMSE started to increase. As judged

Table 5 Evaluation of tested ANN’s based on (RMSE) value

No. of neurons	One hidden layer (RMSE)	Two hidden layers (RMSE)
2	0.206	0.308
3	0.193	0.21
4	0.188	0.196
5	0.183	0.191
6	0.174	0.188
7	0.1091	0.179
8	0.10173	0.183
9	0.10172	0.19
10	0.10168	0.192
11	0.10176	0.195
12	0.10179	0.197

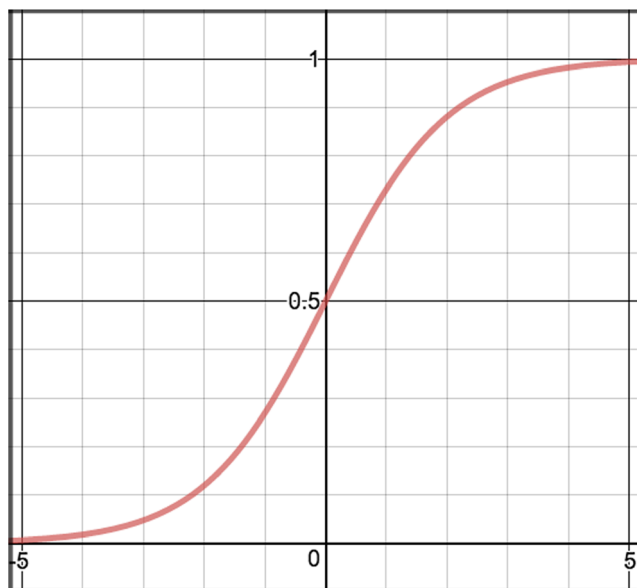
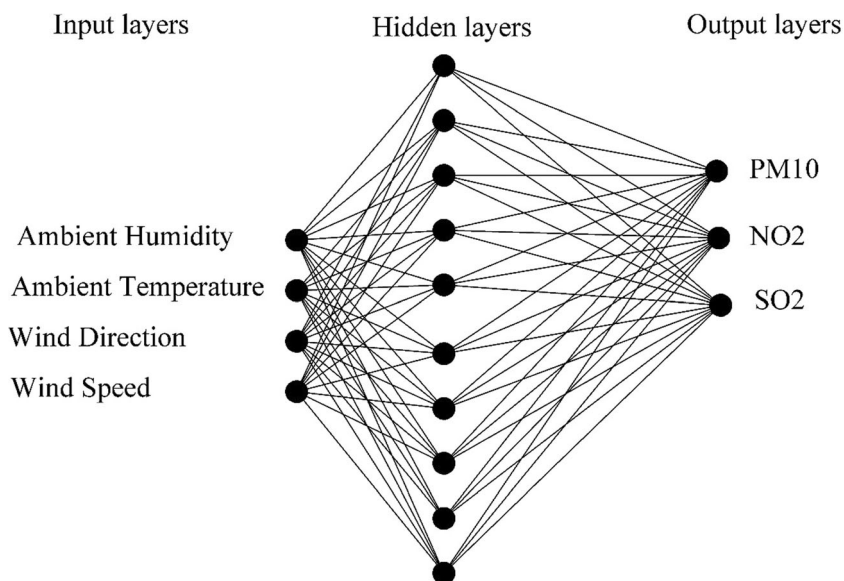


Fig. 3 Graphical description of the used activation function (MATLAB, 2018)

by RMSE values presented in Table 5, the optimal number of the hidden layers is one layer with ten neurons, as this corresponds to a minimum RMSE value of 0.10168 (Fig. 3).

The activation function selected was a sigmoid function as it is the most appropriate function in the case of air pollution (Cabaneros et al., 2019). Therefore, the ANN structure [4-1-3] was selected with 10 neurons in the hidden layer. Figure 4 shows the structure of the developed ANN that was used in predicting the concentration of air pollutants. Based on the first scenario (baseline scenario) which assumes no pandemic took place, data for the year 2019 (from January 1, 2019, to December 31, 2019) was used in the ANN model development to predict the emissions

Fig. 4 Structure of the developed ANN model



for the first quarter of 2020 (from January 1, 2020, to April 13, 2020). Figure 4 (left) shows the predicted versus actual emissions values for NO₂ without the COVID-19 pandemic scenario (business as usual).

It can be seen that the predicted values in 2020 are always higher than the actual measured values of the air pollutants concentration, which implies that the model is always overestimating the values of emissions. Similar results were found by Sáez et al. (2018), who reported that the ANN model always overestimated the low values of water runoff. On the other hand, Fig. 5 (right) shows that the model predicts the NO₂ concentration during the pandemic period with good accuracy.

This is also confirmed by the values of coefficient of determination as shown in Fig. 6, where it is 0.38 for the without pandemic scenario and 0.82 for the with the pandemic scenario. Mean absolute error (MAE) which measures the average magnitude of the errors in a set of predictions was also computed for the two scenarios. Many researchers used MAE; for example, Tzani et al. (2019) and Diaz-Robles et al. (2008) used MAE and RMSE to check the accuracy of their ANN models. In the current study, the results showed that MAE for the without pandemic scenario was 10.33 while it was 1.88 for the with the pandemic scenario which means that the pandemic scenario is more accurate than the other scenario. This is in agreement with the findings of several researchers in other countries. For example, Higham et al. (2020) reported that the nitrogen oxide levels across the country dropped substantially (by approximately 50%), during the COVID-19 lockdown in the UK. Singh and Chauhan (2020) also reported a decrease in NO₂ concentration during the lockdown in India, while Gautam (2020) reported a reduction in NO₂ atmospheric concentration during the lockdown in several Asian and European countries.

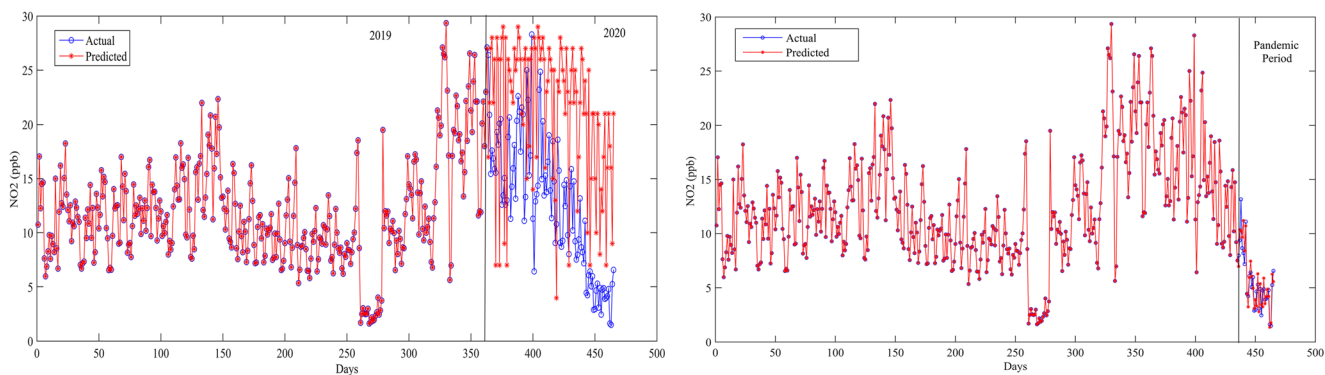


Fig. 5 Actual and predicted NO₂ concentrations (ppb) (left: no COVID-19 pandemic scenario; right: with COVID-19 pandemic scenario)

Figure 7 (left) shows the predicted versus actual emissions values for PM₁₀ without coronavirus pandemic scenario (business as usual) and with pandemic scenario (right). It can be observed from Fig. 7 that the model has good predictability of the PM₁₀ values during the pandemic period as judged by the value of the coefficient of determination which was found to be 0.86, while without pandemic, the value of the coefficient of determination is 0.52 as shown in Fig. 8.

Similar results were obtained for SO₂ as shown in Fig. 9. The coefficient of determination values for the pandemic period was found to be 0.81 for SO₂.

Conclusions and recommendations

The impact of the lockdown policy due to the spread of coronavirus pandemic on the air quality in the city of Irbid

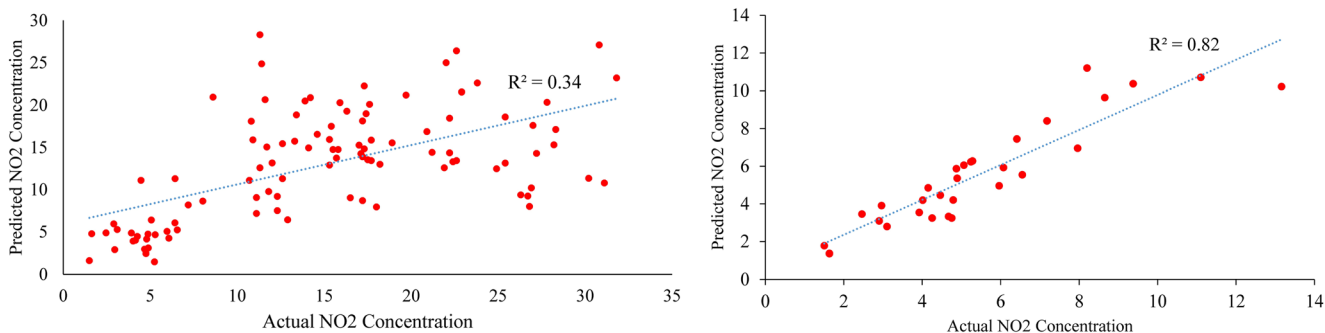


Fig. 6 Actual vs predicted NO₂ concentrations (ppb) (left: no COVID-19 pandemic scenario; right: with COVID-19 pandemic scenario)

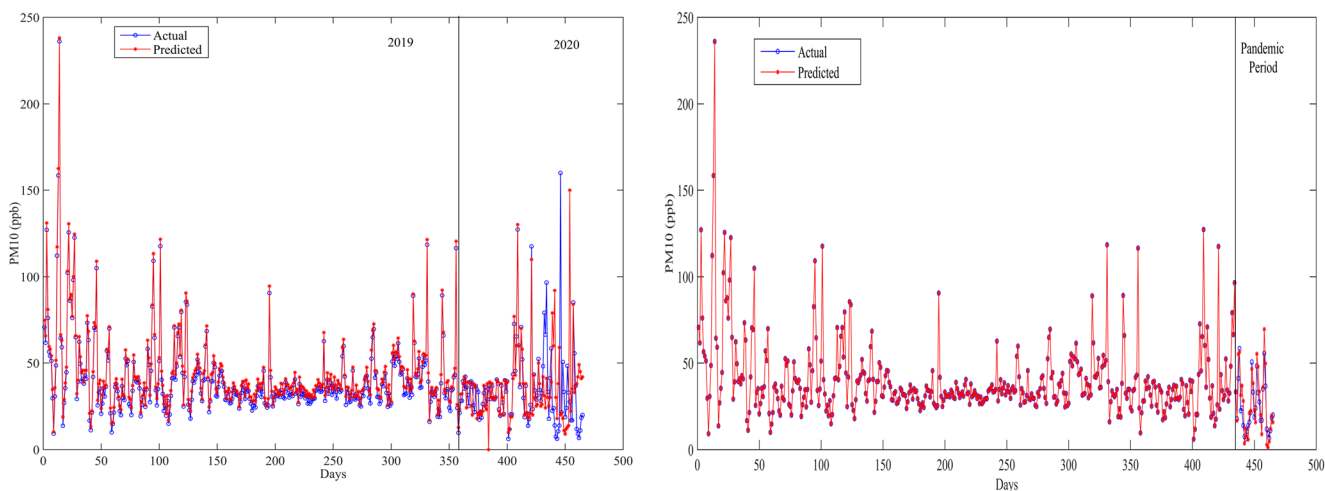


Fig. 7 Actual and predicted PM₁₀ concentrations (ppb) (left: no COVID-19 pandemic scenario; right: with COVID-19 pandemic scenario)

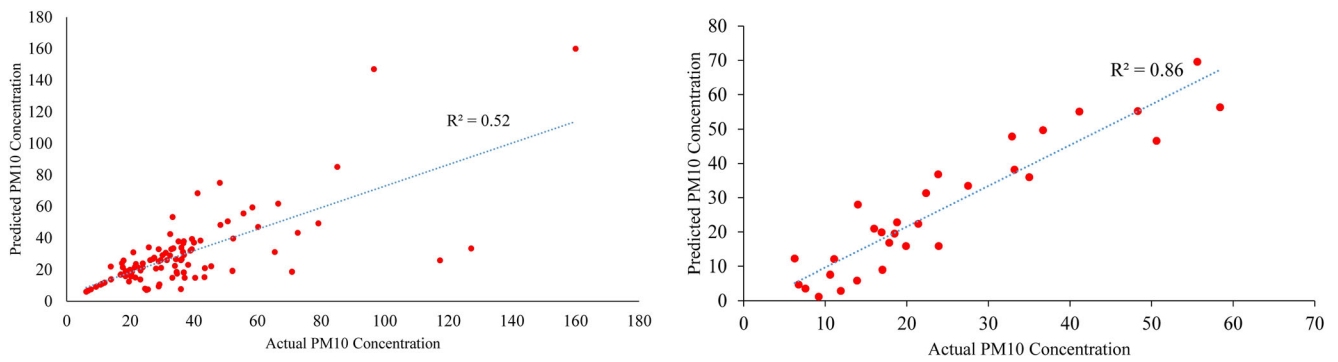


Fig. 8 Actual vs predicted PM_{10} concentrations ($\mu\text{g}/\text{m}^3$) (left: no COVID-19 pandemic scenario; right: with COVID-19 pandemic scenario)

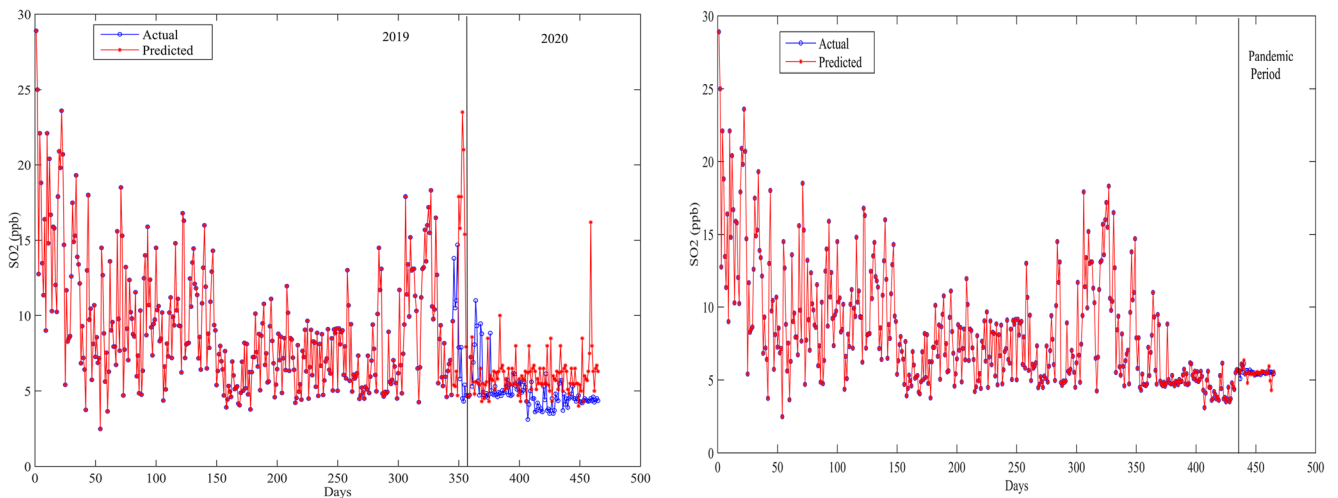


Fig. 9 Actual and predicted SO_2 concentrations (ppb) (left: no COVID-19 pandemic scenario; right: with COVID-19 pandemic scenario)

(northern Jordan) was analyzed and modeled using ANN. Three pollutants were studied (NO_2 , SO_2 , and PM_{10}) based on two scenarios, namely, with and without the spread of the coronavirus pandemic. The analysis revealed that all the studied pollutants concentrations are within the limits imposed by the Jordanian Standard of Ambient Air Quality. The concentrations of all pollutants were declined during the pandemic period with different percentages. Among the studied pollutants, NO_2 has the largest decline of 72%, while PM_{10} has the lowest with a decrease of 29%.

Based on the measured data from one air quality monitoring station in Irbid city, it was possible to develop an ANN model with meteorological data during the year 2019 fed as an input to the model to predict the concentration of the three studied pollutants. Based on the coefficient of determination, the developed model could predict the variability in the concentration of the pollutants during the spread of the coronavirus pandemic with different percentages 81%, 82%, and 86% for SO_2 , NO_2 , and PM_{10} respectively. In this paper, the

emissions studied were mainly from a traffic source, further studies are recommended to predict the air pollutants during the pandemic period in cities with emissions from industrial sources.

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Authors' contributions N. Shatnawi compiled, analyzed, and interpreted the data and participated in the manuscript preparation. H. Abu Qdais performed the literature review, interpreted the data, and prepared the manuscript text and manuscript edition.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Compliance with ethical standards

In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication

and/or submission, and redundancy have been completely observed by the authors.

Conflict of interest The authors declare that they have no conflict of interest.

Code availability Not applicable.

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