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Air Quality Assessment and Forecasting Using Neural Network Model

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ABSTRACT

Air pollution is a major obstacle faced by all countries which impacts the environment, public health, socioeconomics, and agriculture. In this study, the air pollutants in the city of Amman were presented and analyzed. Nonlinear Autoregressive Exogenous (NARX) model was used to forecast the daily average levels of pollutants in Amman, Jordan. The model was built using the MATLAB software. The model utilized a Marquardt–Levenberg learning algorithm. Its performance was presented using different indices, R^2 (Coefficient of Determination), R (Coefficient of Correlation), NMSE (Normalized Mean Square Error), and Plots representing network predictions vs original data. Historical measurements of air pollutants were obtained from 4 of the Ministry of Environment (MoEnv) air quality monitoring stations in Amman. The meteorological data representing three years (2015, 2016, and 2017) were used as predictors to train the Artificial Neural Network (ANN) while the data of the year 2018 were used to test it. The results showed good performance when forecasting SO_2, O_3, CO, and NO_2, and acceptable performance when forecasting Particulate Matter (PM10) at the given 4 locations.

Keywords: air pollutants, ANN, MATLAB, forecasting

INTRODUCTION

The industrial revolution was introduced in the mid of 19th century and brought along with it the age-of-smoke (Mosely, 2014) by presenting new sources of air pollution. The development of steam engine contributed massively in this revolution. Development of transportation, cultural behaviors of consumers, improved living standards, and working conditions were changed with noticeably rapid increment. Human beings emitted greater amount of carbon dioxide to the atmosphere in the past 150 years than they did for hundreds of thousands of years (Nunez, 2019). In 1952, the smog in London claimed 8000 peoples' lives (Renewable Resources Co, 2016). This event was caused by periods of cold weather along dense layers of airborne pollutants, mostly from coal plants in the city, an episode known by the name "Great Smog" (Mosely, 2014). According to the World Health Organization (WHO) report on ambient air pollution and health impacts, in 2016 bad outdoor air caused almost 4.2 million premature deaths globally. In the US, over 40% of the population are at risk of premature death in addition to the associated risks due to increased air pollution. Countries around the world are being more aware towards the adverse impacts of pollutions and gas emissions. For example, in 1990 the US Congress passed the Pollution Prevention Act (PPA) to reduce the amount of toxins released into the environment (Burnett, 1998). In 1992, an international convention, the United Nations Framework Convention on Climate Change (UNFCCC) or "Earth Summit" that aims mainly to accomplish stabilization of greenhouse gases (GHG) levels in the atmosphere at a concentration level that would avoid hazardous interactions with the environment. The Paris Agreement and the Kyoto Protocol are equally famous treaties towards the act of pollution prevention, as they are extensions to the Earth Summit (Ramakrishna, 2000).

Literature survey demonstrates that there are several approaches to forecast the air quality, reaching from numerical, mathematical, statistical methods and comparative analysis of energy and emission indicators (Al-Hinti et al., 2013), to artificial intelligence practices, specifically Artificial Neural Networks (ANN). Forecasting and modeling of air quality as well as environmental constraints is of major importance for studies and has been performed including several approaches, starting by atmospheric diffusion models to predict future emissions, or even the numerous statistical models that attempt to determine the relationship between sets of raw data (or pre-processed original data) and target data. However, due to their lack of flexibility to convey the complexity and non-linearity of pollution and relationships between meteorological parameters, in addition to advancing technology and growing computer aided analysis procedures, Artificial Neural Network models proved useful and promising in handling complex and non-linear systems. Types of ANN include the back-propagation neural network (Yi J. and Prybutok V., 1996), multilayer perceptron (Gardner M. and Dorling S., 1998; Wang D. and Lu W-Z, 2006; Durão et al., 2016), radial basis function (Iliyas et al., 2013), and adopted neuro-fuzzy inference systems (Prasad et al., 2016). Numerous studies have evaluated various aspects of $PM_{2.5}$ and PM_{10} mass concentration in different areas such as the city of Santiago, Chile (Perez P., 2001; Perez P. and Reyes J. 2002) India (Patra et al., 2016) and Portugal (Russo et al., 2015). Among the applications of ANN for air pollution research was forecasting the NO_2 and NOx (Gardner M. and Dorling S., 1999), SO_2 levels (Perez P., 2001; Tecer L., 2007), CO_2 levels (Baareh 2013; Sangeetha A. and Amudha T., 2018), O_3 concentrations (Hassan A. M. and Dong Z., 2018), and N_2 levels (Sabri G. and Tarek K. 2009). Only one study was conducted in Jordan where researchers exploited the daily average meteorological parameters constructed from relative humidity, wind speed, and mean temperature to forecast PM_{10} and TSP (total air suspended particles) in the city of Al-Salt, Jordan over the period between November 2006 and November 2007 (Alkasassbeh M. et al., 2013)

STUDY AREA

Amman is the capital and largest city of Jordan. According to the Department of Statistics (DoS) population estimates report of 2018, over 10 million people reside in Jordan, whereas more than 42% of the Jordanian population, that is approximately 4.33 million residents, live in the capital, Amman. This document has highlighted Amman as the subject of concern due to the highest population count on a specified area of 1,680 km² representing a percentage of only 1.88% of the total area of the country (Department of Statisics, 2018).

The Jordanian fuel consumption is following an increasing linear trend, as the consumption grew from 7.03 million ton in 2005 to 10 million tons in 2018, as Figure 1 shows (Nepco, 2017). According to WHO, Amman yearly average concentration of PM_{10} is 68 µg/m^3, which is very high when compared to the standard recommended by WHO at 20 µg/m^3 as annual average (WHO, 2016).

The quantity of total municipal solid waste (MSW) based on the latest DOS reports of 2017 in Amman is 1.54 million tons which is 46% of the total country waste. Considering nearby areas of Amman, the total MSW accounted for 2.25 million tons, in the middle region. On the basis of EPA 1995a, 1997, and AP-42 emission ratio, each ton of open burning of MSW will generate 1 lb of SO_2, 85 lb of CO, 13 lb of CH4, 6 lb of NO, 8.556 lb of VOCs, and 38 lb of PM10. Another factor affecting the air quality in Amman

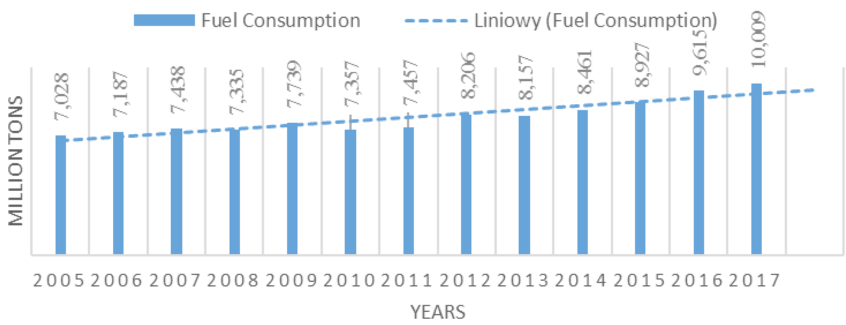

Figure 1. Fuel Consumption in million tons

is the industry surrounding the city specifically that of Zarqa, as it is home to around 35% of the heavy industrial business in Jordan. Fuhais, 15 km away from Amman, is home to most of cement production industrial activities in the country, with production size of over 2 million tons per year. Cement production fills the air with a variety of pollutants, such as soot, hydrocarbons, sulfur compounds, nitrogen oxides, and carbon oxides. On a lesser scale, the lack of organized waste management and heating systems worsen the air quality as well. All the above factors are worsened by the fact that Amman is set on 19 peaks, which traps unhealthy, polluted air. In addition, the city is struck by unpredictable dust storms. More so, Amman as a city lacks proper green places and is full of buildings, mainly 4 story ones. Because of unplanned and unorganized urbanization, housing is sprawling (Hadadin & Tarwaneh, 2007), and green areas are diminishing inside the city of Amman along with its surroundings, due to shocking urban expansion rates (Al Rawashdeh & Saleh, 2006).

The Ministry of Environment has a major task in monitoring the air pollutants levels in the Jordanian atmosphere in accordance to the Environmental Protection Law No. 6 of 2017 and Air Protection Law No. 28 of 2005. The levels are compared to the Jordanian Air Quality Standard (JS 1140/2006) in order to take effective measures in case the standards have been violated. In order to accomplish such a task, a national air quality monitoring system consisting of 12 stationary monitoring stations has been established. The stations have been distributed and set up in industrial areas, and the areas characterized with heavy traffic. KHG, is the main monitoring station and considered as reference for all other stations. The stations are distributed as shown in Table 1, whereas the stations highlighted with yellow are the ones that will be considered for the purpose of this research. All equipment used for air quality monitoring in all stations are accredited by U.S EPA and other European organizations and comply with the JS 1140/2006.

This study is established to forecast the pollutants concentration in Amman city based on historical pollutant measurements and the meteorological data collected from four out of the twelve stations distributed mainly in Amman, Irbid, and Zarqa governorates. The air quality is monitored round the clock, and 24-hour average reports of measurements are announced daily on the MoEnv website (Ministry of Environment, 2019). This data was utilized in this study for the purpose of designing a neural network model in MATLAB to forecast future concentrations of pollutants. This study is motivated by the need to identify the air pollution concentrations in advance. More so, the investigation on air pollution forecasting can prove vital in providing the basis for policy makers to draft scientific, rational, and economic advancement legislations. Apart from one study analyzing and forecasting air pollution in Jordan, in the city of Al-Salt, there is a research gap as well as lack of studies concerning air pollution forecasting and air quality addressing Jordan in general, and Amman in specific. To the best of the author's knowledge, this work has not been previously conducted.

METHODOLOGY

This work focused on the data collected from 4 stations located in the city of Amman between

Table 1. Pollutants measured in each station

Abbreviation	Station Type	Station Name	PM10	O_3	SO_2	NO_2	CO	Climatic Parameters
Amman								
KHG	Reference	King Hussein Gardens	•	•	•	•		•
GAM	Urban	Greater Amman Municipality	•		•	•	•	
MAH	Urban	Marka - Mahatta	•		•	•		
UNI	Traffic	University Street - Sweileh	•			•		
KAC	Industrial	King Abdullah II Industrial City / Sahab	•		•	•		•
YAR	Industrial	Wadi Rimam - Yarmouk Garden	•		•	•		•
TAB	Traffic	Northern Bus Station - Tabarbour	•			•	•	•
Zarqa								
HAJ	Traffic	Health Center Wadi Hajjar	•		•	•	•	•
MAS	Industrial	Main Slaughter House - Masane' Zone	•		•	•		

January 1st, 2015 and December 31st, 2018. The forecasting task was carried out using artificial neural networks in MATLAB. The results were reported based on Mean Square Error (MSE), Coefficient of Determination (R squared), and Normalized Mean Square Error (NMSE), plus Plots comparing the values between observed and predicted measurements. The KHG station was used as a reference station to describe the relation between the meteorological parameters and PM_{10}, NO_2, SO_2, O_3, and CO. Although the KHG station is not equipped with a device to measure the CO levels, its data is summoned from the GAM station. KHG has an extra device to measure some meteorological parameters as well, namely Ambient Temperature (°C), Ambient Humidity (%), Wind Direction (degrees), and Wind Speed (km/h). As a first step, the effect of Temperature, Humidity, Wind Speed, and Wind Direction was studied separately to check if these parameters affect the pollutants and consequently used as input parameter in the neural network model.

Temperature and Humidity

The annual average temperature in Amman is around 15.7°C and the city is characterized by hot weather in summer and cold weather in winter. The unprocessed data of temperature, NO_2, O_3, and SO_2, are plotted as monthly averages in order to visualize how the pollutant concentrations differ within the year with varying temperature. The X-axis represents the month and the year of collected data, and the Y-axis represents the average value of the pollutants in parts per billion (ppb) and the average temperature in degrees Celsius (°C). Figure 2a reveals that as ambient temperature increases, only ozone level increases while NO_2 and SO_2 levels decrease. In general, the graph clearly shows that during hot months the ozone levels are high, while the NO_2 and SO_2 levels are low. Conversely, in cold months the relation is reversed. In order to clearly identify the relation between temperature and PM_{10}, a scatter plot was usedm as shown in Figure 2b, where the Y-axis represents the daily values of PM_{10} between 0 and 120 μg/m^3 representing the allowable range as per the Jordanian standard and not taking the full range of PM_{10} in order to zoom in on the relation and be seen clearly. The X-axis represents the full range of temperature. Using this graph, now, it is visibly shown that the PM_{10} levels increase slightly along with ambient temperature, as expressed by the trend-line (MoEnv, 2018). The relation of CO against temperature could be visualized using the scatter plot, Figure 2c. A relation showing that the CO levels slightly increase with temperature, as expressed by the trend-line. The range of CO is taken only between 0 and 4000 ppb to clearly show the relation.

The annual average humidity in Amman is 62.7%. The city is characterized by dry weather in summer and rainy weather in winter. Figure 2d demonstrates an interesting relation between ambient humidity and O_3 formation. The level of O_3 increases when humidity decreases. Additionally, it shows that the NO_2 levels decrease along with humidity, which could be attributed to increasing O_3 formation as explained, because NO_2 acts as a precursor in the formation of Ozone. The SO_2 levels are also decreasing with decreasing humidity. Finally, the graph also shows that the O_3 levels in 2018 are lower than previous years. The scatter plot shown in Figure 2e indicates the PM_{10} values when they were subjected to various humidity levels. As mentioned previously, PM_{10} depends on multiple elements to be created and is highly dependent on meteorological data, especially Humidity. The plot demonstrates that the PM_{10} values decreases as Humidity increases, which is in line with the literature and meteorological measurements. Figure 2f shows the relation between CO and humidity. The figure reveals that CO and humidity have a negative correlation.

Wind Speed and Wind Direction

The scatter plot in Figure 3 a, represents the relation between Wind Speed and PM_{10}, NO_2, SO_2, O_3, and CO. Figure 3 shows that all pollutants are concentrated at low wind speeds.

The wind rose chart in Figure 3b, shows that PM_{10} is more concentrated when the wind is hitting Amman from West and South-West directions. This is self-explanatory, as Amman is characterized with approximately 270 days per year where wind is blowing from the West and South-West directions. Additionally, Amman is hit by several sandstorms (Khamasini-winds) annually that are usually coming from the South or South-West directions. These Khamasini-winds are hot, dry and carry massive amounts of dirt and dust with it that complements the city with huge amounts of particulate matter.

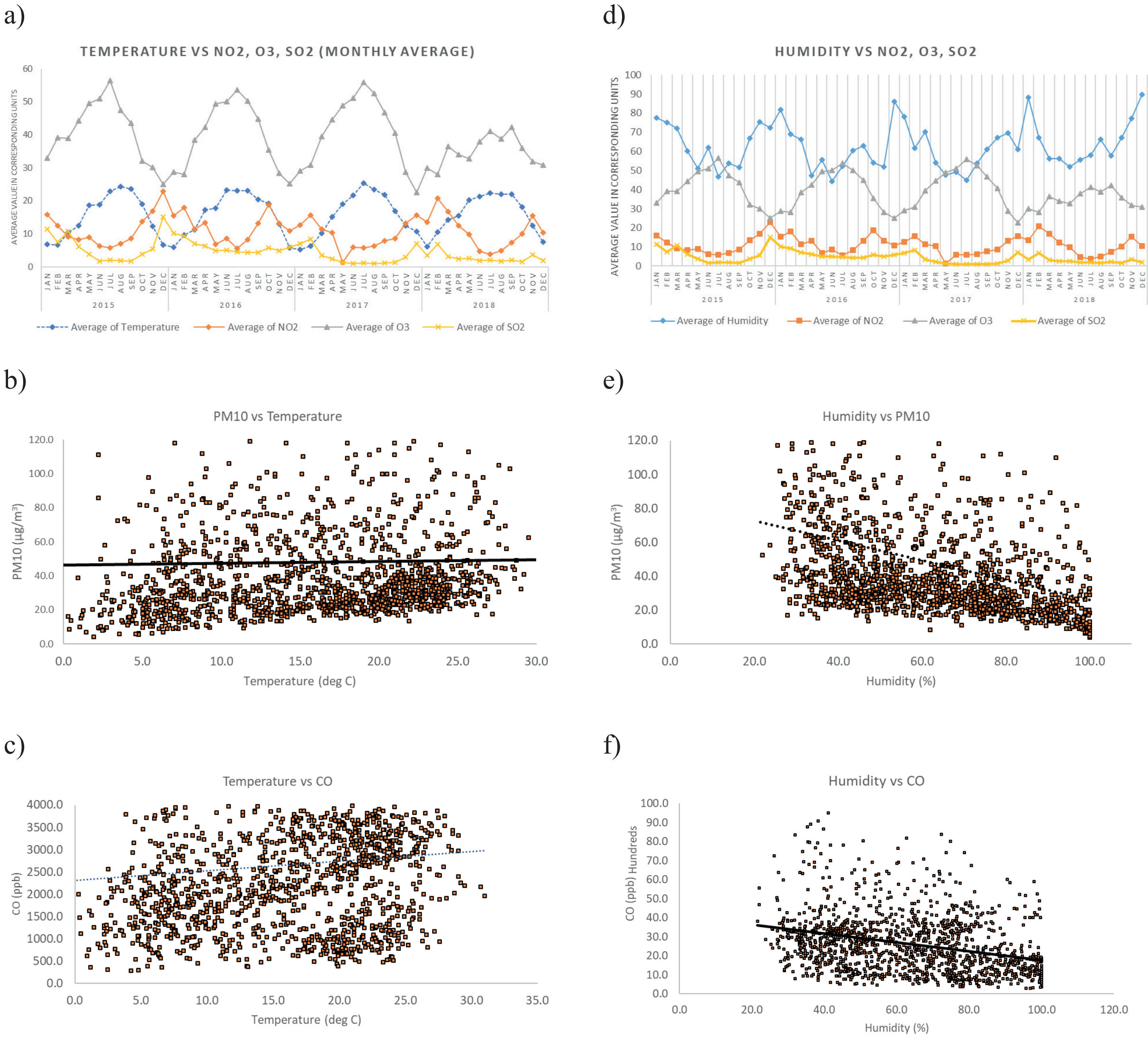

Figure 2. Pollutants versus temperature and humidity

DATA PREPROCESSING

The data has been attached to its correct date value to achieve a uniform date scale between 1 and 1460 indices for all stations in order to match that of the meteorological parameters. The collected data has few missing values, as shown in Table 2. The missing values were excluded from the study because the other alternative which is linearly interpolating the missing value will not lead to accurate results since air pollution is not predictable and interpolating its values between two extremes (lower and higher) means to strictly put the values inside this range. Then, the data was checked for outliers which were kept without being removed because the air pollution levels are random in nature, specifically when related to meteorological parameters.

Afterwards, data was normalized using the min-max normalization method in MATLAB where data is converted into a range of 0 – 1, using the following formula:

$$X_{nor} = \frac{X - min.}{max. - min.}(max._{new} - min._{new}) + min_{new} \quad (1)$$

where: X_{nor} is the normalized value,
X is the original value,
$min.$ and $max.$ are the original minimum and maximum values, respectively,
$min._{new}$ and $max._{new}$ adhere to the range of preference (in this study it is 0 – 1).
Then, after training ends, the data is de-normalized to be plotted using original scale (Li, Jin, & Jin, 2015).

After processing the data, a Series-Parallel type of NARX modeling is used. The dataset is

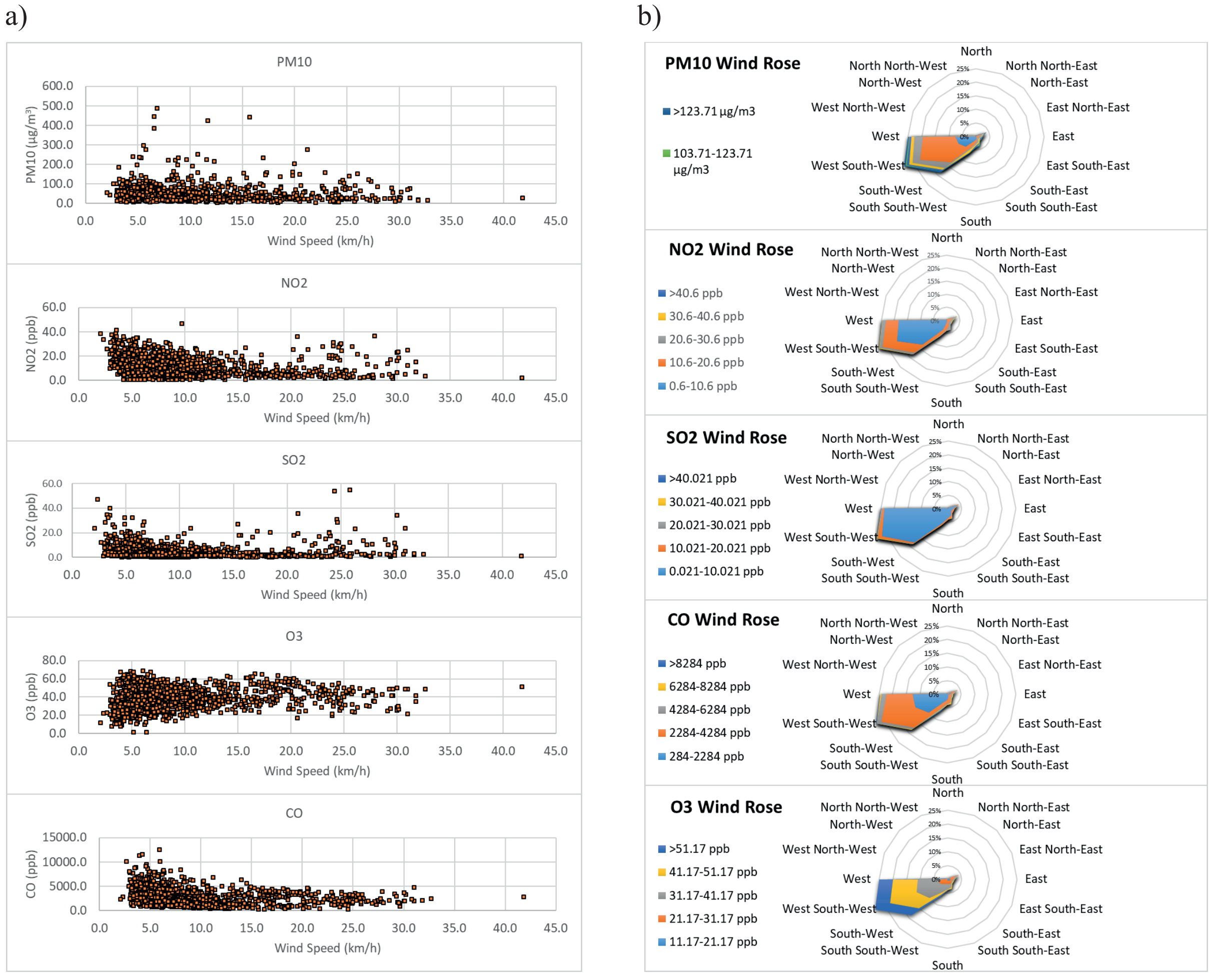

Figure 3. Pollutants versus wind speed and wind direction

first introduced to the model, which separates the variables into inputs and output. After that, the inputs and output are divided into two sets of data. The first involved training, which includes that data of the years 2015 to the end of 2017. The second was for model testing, and it includes the data of the year 2018. Then, the data was normalized as explained previously. This data was divided into 3 blocks (70% for training, 15% for Validating, and 15% for Testing) inside the network topology using the DIVIDEBLOCK function, which is useful for preserving the time sequence of the series. Only the training set of the data is used to update the network weights and biases. The validation set is only there to ensure the best performance on new data, and the test set is only used to test the network. Although there is no need for a new separate set of data for testing, as explained above, the data of 2018 acts as a fresh new set of unseen data to be predicted and provide visual comparison between the predicted values and original ones. Afterwards, using the size of the input and target series, the number of training examples is calculated in order to find the number of training equations. This is done in order to avoid overfitting the network. Because, overfitting of the network occurs when the number of unknown weights exceeds the number of training equations.

Table 2. Number of missing values in each station

	PM10	NO_2	SO_2	O3	CO	Humidity	Temperature	Wind Speed	Wind Direction	Valid N
KHG	2	21	1	0	-	6	16	13	13	1414
GAM	15	19	4	-	26					1383
UNI	2	6	-	-	-					1426
MAH	52	72	236	-	-					1163

The network is created using the training data set (2015–2017) and trained iteratively between the minimum number of hidden nodes, which is 0 and resulting in an I-O (input-output) network architecture, up to the maximum number of hidden nodes, which is reliant on the number of training equations and the size of the datasets. When hidden nodes are introduced to the network, it becomes an I-H-O (input-hidden-output) type of neural networks. The purpose of iterating the training phase is to achieve best performance, or in other words the minimum gradients of all iterations. The network is trained based on Levenberg-Marquardt backpropagation, "trainlm". This type of training function usually offers minimum training-time requirements in supervised algorithms. The hidden layer utilizes a TANSIG (Hyperbolic tangent sigmoid activation function), and the output layer utilizes a PURELIN activation function, which is a linear transfer function, used to calculate the output of the network. The network is also configured to avoid overfitting, as explained above, and its performance is reported using Mean Square Error (MSE). MSE is then used to report the network function using R^2 (Coefficient of Determination) and Normalized Mean Square Error (NMSE).

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(NetworkErrors)^2 \qquad (2)$$

$$NMSE = \frac{MSE(Network\ Errors)}{mean(variance\ of\ TargetSeries)} \qquad (3)$$

$$R^2 = 1 - NMSE \qquad (4)$$

After training of the network, it is transformed to a closed loop network in order to be introduced with the testing dataset. After the closed loop network is simulated, the data is denormalized to its original scale. Then, the network predicted outputs are plotted against test target data to show performance of the model. Finally, if the closed loop suffered reduced performance, it is trained again using the initial open loop weights in order to serve better predictions. The final results are plotted again to show improvement.

It was chosen to forecast the pollutants using the meteorological parameters of Humidity, Temperature, Wind Speed, and Wind Direction, along with day of year. These parameters will act as independent inputs (exogeneous) for the network. The target dataset will also act as a second input used with a feedback signal of 1, in order to predict the next time step (at t+1) using present meteorological parameters (at t), present pollutant value (at t), and 1 timestep-delayed pollutant value (at t-1). In the case of PM_{10}, an extra case is shown, where all other readings by the station will be attached to the meteorological inputs, introduced to the network with an initial delay of 1. That is because PM_{10} is a combination of most, if not all the pollution constituents in the atmosphere.

RESULTS AND DISCUSSION

Time, Wind Speed, Wind Direction, Humidity, and Temperature were used as independent inputs to forecast NO_2, SO_2 and CO, whereas Meteorological Parameters + NO_2, SO_2, and CO were used as inputs to forecast PM_{10}. NMSE and R^2 are reported in Table 3 for all the stations. The regression of the model is shown in Figure 4 for the GAM station. Figure 5 shows the results (test data vs predicted data) after re-training of closed loop using the initial weights of open loop model for GAM station.

For NO_2, a correlation factor (R) between model inputs and its estimated output is R=0.94 for training, 0.78 for validation, 0.53 for testing, and overall R=0.86.). After re-training of closed loop using the initial weights of open loop model, the prediction results improved with an NMSE = 0.26 and R^2 = 0.74. As shown by the results and graphs above, in the case of the GAM station, forecasting NO_2 using the proposed model gave good results. It is shown that the performance of the network deteriorated after closing the loop, which was corrected by re-initializing the closed circuit by the model initial weights. This showed improvement in the performance of the model and produced a good prediction fit.

Regarding SO_2 forecasting, the correlation factor (R) between model inputs and its estimated output is R=0.86 for training, 0.73 for validation, 0.83 for testing, and overall R=0.65. The closed loop performance reached an NMSE of 0.62 and R^2 =0.37. The closed loop was trained again using the initial weights of open loop model. The prediction results improved with an NMSE = 0.40 and R^2 = 0.59. The results above show that using

Table 3. Performance criteria for pollutants forecasting

Station		NO_2		SO_2		CO		PM10 using Meteorological Parameters Only		PM10 using Meteorological Parameters + NO_2, SO_2, and CO	
		NSME	R^2	NSME	R^2	NSME	R^2	NSME	R^2	NSME	R^2
GAM	Training	0.1358	0.8642	0.4143	0.5857	0.1178	0.8822	0.6304	0.3696	0.6365	0.3635
	Validating	0.2173	0.7827	0.6886	0.3114	0.5699	0.4301	0.1084	0.8916	0.3826	0.6174
	Overall	0.2845	0.7155	0.6203	0.3797	0.3027	0.6973	0.5086	0.4914	0.7130	0.2827
						O_3					
KHG	Training	0.1775	0.8225	0. 3392	0. 6608	0.4560	0.5440	0. 9065	0. 0935	0.8790	0.1210
	Validating	0.7965	0.2035	0. 5625	0. 4375	0.3057	0.6943	0. 1324	0. 1324	0.9180	0.0820
	Overall	0.4381	0.5619	0.4742	0. 5258	0.4349	0.5651	0. 6997	0. 3003	1.1525	-1.6708
UNI	Training	0.1894	0.8106	-	-	-	-	0.9252	0.0748	0.7690	0.2310
	Validating	0.5119	0.4881	-	-	-	-	0.1615	0.8385	0.1582	0.8418
	Overall	0.3718	0.6282	-	-	-	-	0.7371	0.2629	0.6331	0.3669
MAH	Training	0.2926	0.7074	1.0953	-0.0953	-	-	0.6046	0.3954	0.7303	0.2697
	Validating	1.2462	-0.2462	2.0353	-1.0353	-	-	0.1275	0.8725	0.2568	0.7432
	Overall	0.8570	0.1430	1.4843	-0.4843	-	-	0.4803	0.5197	0.6141	0.3859

the proposed model to forecast SO_2 at GAM station resulted in marginally acceptable results. The performance of the closed loop was enhanced slightly after re-training.

CO was forecast using the same inputs. The network topology is the same as that for NO_2. The correlation factor (R) between model inputs and its estimated output is R=0.92 for training, 0.81 for validation, 0.86 for testing, and overall R=0.87. The closed loop performance reached an NMSE of 1.22 and R^2 = -0.22. Figure 28 shows the result of the closed loop network prediction and compares it to the test data of 2018. The closed loop was trained again using the initial weights of open loop model. The prediction results improved with an NMSE = 0.58 and R^2 = 0.42. The results presented above show a rather interesting event, where the R^2 is reported to be negative. Mathematically, this is completely illogical. However, when dealing with software programming, a negative R^2 performance seems to simply represent a BAD fit, from a statistical point of view. It could also be due to some bias in the model towards a negative correlation with input parameters. This was enhanced after re-training the closed loop, resulting in an acceptable positive performance, and a slightly enhanced model prediction fit.

PM_{10} was forecast using the same parameters. The correlation factor (R) between inputs for the model and its estimated output of R=0.73 for training, 0.40 for validation, 0.48 for testing, and overall R=0.71. The closed loop performance reached an NMSE of 0.83 and R^2 = 0.16. The closed loop was trained again using the initial weights of open loop model. The prediction results did not improve and remained the same at an NMSE = 0.83 and R^2 = 0.16. The results show that predicting PM_{10} using meteorological parameters only, at the GAM station, by means of the proposed model, resulted in a bad fit. Retraining the closed loop had absolutely no effect on the performance. The inputs were adjusted by adding NO_2, SO_2, and CO as extra variables in the input parameters. The regression of the model shows a correlation factor (R) between inputs for the model and its estimated output of R=0.77 for training, 0.48 for validation, 0.30 for testing, and overall R=0.66. The closed loop performance reached an NMSE of 01.0046 and R^2 = -0.0046. The closed loop was trained again using the initial weights of open loop model. The prediction results improved and reached an NMSE = 0.66 and R^2 = 0.34. Predicting PM_{10} using extra inputs at GAM station, resulted in slightly improved performance.

CONCLUSIONS

The task of forecasting the levels of air pollutants in the city of Amman was carried out using MATLAB for 5 air pollutants monitored at 4 stations. The forecasting task was carried out using the NARX artificial neural network. The performance of the model was presented using R^2, NMSE, and timeseries plot representing network prediction outputs against original test series. The

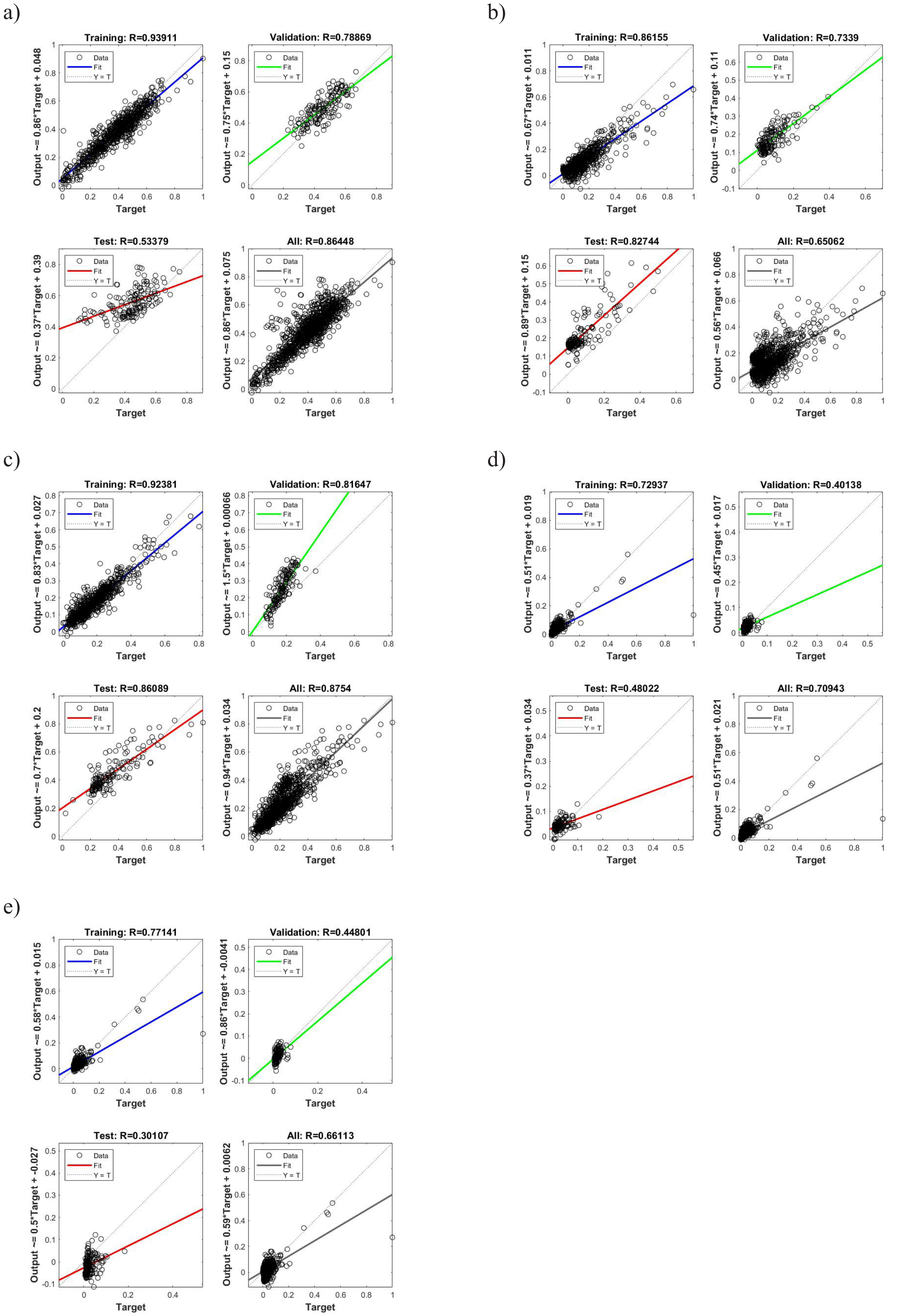

Figure 4. GAM station Training/Regression/ Forecasting

a) Training Regression of NO_2 Forecasting/GAM/Meteorological Inputs, b) Training Regression of SO_2 Forecasting/GAM/Meteorological Inputs, c) Training Regression of CO Forecasting/GAM/Meteorological Inputs d) Training Regression of PM10 Forecasting/GAM/Meteorological Inputs, e) Training Regression of PM10 Forecasting/GAM/Meteorological Inputs + Pollutants

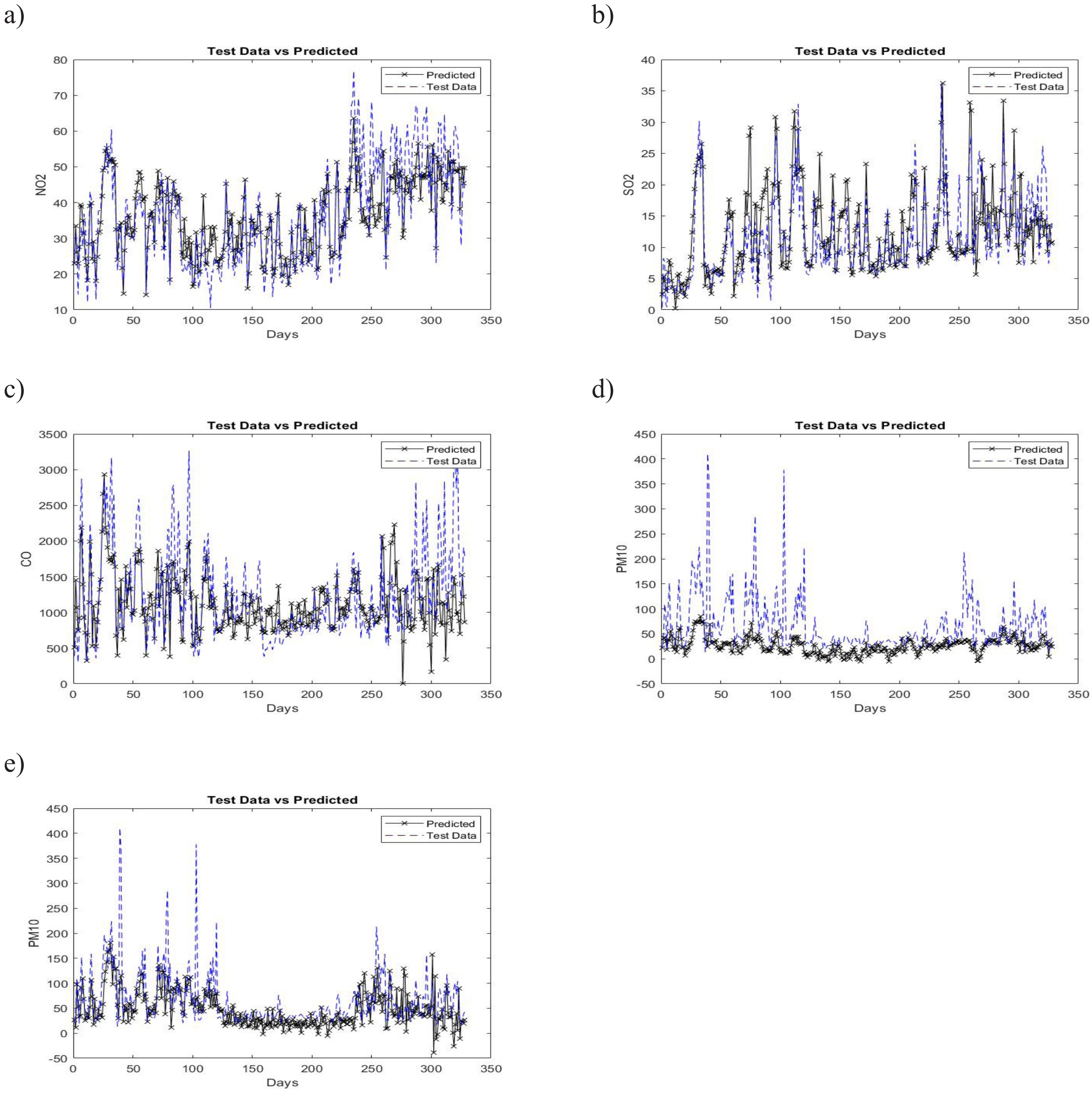

Figure 5. GAM station Predictions after Retraining of Closed Loop

model adopted an iterative approach in order to train the model up to a specified performance goal. The model showed good and acceptable performances when forecasting CO, SO_2, O_3, and NO_2.

Overall, the model proved that air pollutants can be predicted with very good accuracy using artificial neural networks. However, its prediction performance will always deteriorate the further the timesteps required to be predicted. Additionally, the model shows the complexity of forecasting the pollutants using only Humidity, Temperature, Wind Speed, and Wind Direction. It shows the need for other parameters that could show better correlation factors between predictors and predictands. The study reveals that the authorities of urban air quality and decision makers can apply ANN to forecast the pollutant concentrations and air quality indices.

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