

# Neural and Mathematical Predicting Models for Particulate Matter Impact on Human Health in Oman

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**Abstract:** - The recorded reports of the World Health Organization (WHO) show that a total of 4.2 million death cases is due to exposure to PM<sub>2.5</sub> particulate matter. This paper aims to analyze and examine the impact of particulates (PM<sub>2.5</sub> and PM<sub>10</sub>) on human health in Oman. Also, it proposed neural and mathematical prediction models for predicting predict the future levels of particulate matter (PM<sub>2.5</sub> and PM<sub>10</sub>) and its influence on human health. The paper performs a critical comparative study of proposed models, which is evident that the proposed models were fast, cheap, and accurate. The first model is based on Linear regression that obtained results of the coefficient of determination  $R^2=0.7604$ , mean square error (MSE=0.0673), and root mean square error (RMSE=0.2595). The second model is based on non-linear regression polynomial that achieved excellent results of ( $R^2$ ) value of 0.9394 and (MSE) value of 0.0209 and (RMSE) value of 0.1447. The Neural model is more accurate in predicting the experimental results, which is obtained the highest achievements of MSE value =0.0064, correlation rate (R) =0.994, and NMSE =0.01392. The work confirmed that the Arab countries and Oman in a good and moderate situation based AQI indicator and did not reach the degree of danger of pollutants.

**Key-Words:** - Environment Impact, Outdoor Air Pollution, Neural Networks, particulate matter, Simulation models.

## 1 Introduction

The concentration of particulate matter (PM) is the most popular air pollutant that affects short term and long term health [1]. The report of the World Health Organization (WHO) shows that the rate of outdoor pollution in developing countries is dramatically increased and will up to 8%. The PM<sub>2.5</sub> particulate matter is a significant cause of premature mortality, with an average of 4.2 million death cases. The PM<sub>2.5</sub> particulate matter causes many diseases such as respiratory, cardiovascular, and cancers. Figure 1 presents the level of PM<sub>2.5</sub> in Oman, which indicates that Onam in Moderate situation [2]. The main sources of air pollution include several resources like energy production (Oil and gas), transportation, and industry, which contribute to increasing the emission rate of pollutants and molecules [3]. Figure 2 presents the sources of air pollution and their relationship with other factors. The main air pollutants include particulate matter, ozone, nitrogen oxides, sulfur oxides, and carbon components, which is reported by World Health Organization (WHO). These pollutants are impacting human health in short-term and long-term effects. The effects of short-term

diseases include cardiovascular, respiratory, cardiovascular, and atherosclerotic diseases.

And, Long-term increased the autism spectrum in children, decreased fetal growth, and low birth weight. Also, elderly patients suffering from various pathological effects like skin and lung cancer, asthma, chronic diseases, and Alzheimer's disease, helping to increase mortality [4]. Increased industrial activity, vehicle emission contribute significantly exacerbated the air pollution problem in some areas of the Sultanate, such as Muscat, Duqm, and Sohar. High temperature and desertification also contribute to high levels of harmful dust, such as PM<sub>10</sub>. Industrial activity in Sohar contributed to the increased risk of air pollution, especially sulfur dioxide from oil refineries [5].

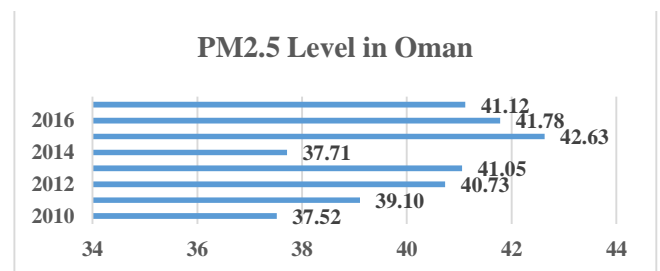


Fig 1. The PM<sub>2.5</sub> level in Oman

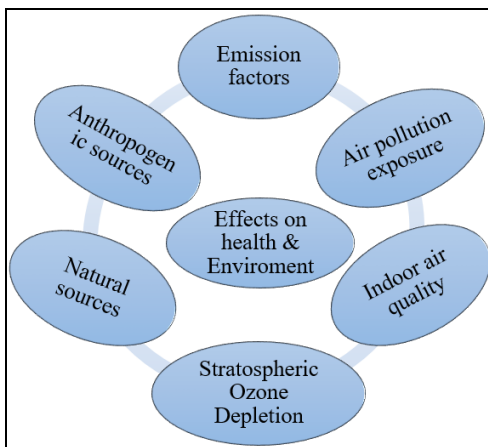


Fig 2. Air pollution sources & relations with other factors

The capital Muscat is also another area that suffers from air pollution resulting from the movement of heavy vehicles and increases the concentration of nitrogen oxide gas (NO<sub>x</sub>). This study provides a method for analyzing the effect of (Particles PM 2.5 and PM 10) and other weather conditions on human and plants life in Sohar using a hybrid neural and mathematical approach. Besides, it will deploy the sensitivity analysis to determine the critical impact factors of particles on human in short and long term conditions [5]. This study suggests a hybrid neural and mathematical approach for analyzing the effect of particulate matter (PM<sub>2.5</sub> and PM<sub>10</sub>) on human health in Oman. Besides, it will deploy the sensitivity analysis to determine the critical impact of each particulate matter that could help to reduce the emission rate.

The study by [6] presented the outdoor and indoor results of PM<sub>2.5</sub> and PM<sub>10</sub> in Doha city and its chemical classification, during two months including regular days and dust occurrences, it was planning to identify the factors affecting the indoor air of an office building. The guideline values of WHO go beyond 100% of the outdoor measurements. 49% of the days are indicated as non-dusty (PM<sub>10</sub> < 200 µg m<sup>-3</sup>), 49% as minor-dusty (200 < PM<sub>10</sub> < 1000 µg m<sup>-3</sup>) while in one case (2%) there was a major-dusty day (PM<sub>10</sub> > 1000 µg m<sup>-3</sup>). Also, another study conducted by [7] several aspects of particulate matter have been analyzed including PM<sub>2.5</sub>/PM<sub>10</sub> ratios and association with meteorological parameters using data collected from January 2014 to September 2015 in Makkah Saudi Arabia. During the study period, 0.64 is the founded mean of the PM<sub>2.5</sub>/PM<sub>10</sub> ratio, whereas median and maximum ratios were 0.69 and 0.99, respectively.

In addition, [8] performed an urban background sampling campaign to measure PM<sub>2.5</sub> pollutants in Sharjah, United Arab Emirates. the major sources of PM<sub>2.5</sub> are fossil fuel burning from traffic and energy

generation which forms the secondary phases formed from gaseous precursors in the absence of dust storm. Also, the work done by [9] revealed that the natural sources such as dust storms crustal matter and seas salts are the main sources caused the rough fraction of PM, while the fine and ultrafine fractions of PM matter contains compounds created through results of the natural rough pollutants with anthropogenic emissions such as sulfur dioxide (SO<sub>2</sub>) and nitrogen oxides (NO<sub>x</sub>), during transport in the atmosphere. An investigation was also conducted by [10] showed the reports on the sources, characterization, and possible mitigation of dust fallout in urban Doha, Qatar. Around 60% of natural origin were identified as the main sources of PM samples, with the balance attributed to anthropogenic sources. The results of a study by [11] demonstrates that the highest critical air pollutants in Bahrain are PM<sub>10</sub> and PM<sub>2.5</sub>. PM<sub>10</sub> dominant during August 2012 and PM<sub>2.5</sub> dominant during January 2012.

## 2 Methods & Martials

### 2.1 Global PM 2.5 and PM 10 Effects

The air quality index (AQI) is a pilot for describing the level of daily air quality. AQI indicates how the air is fresh or contaminated. It determines the effects of air pollution on human health and concludes the time required for the emergence of symptoms of pollution on human health after breathing polluted air. Various areas in the world have recorded extremely high levels of particulates that significantly affect air quality [12]. The World Health Organization's air quality guidelines advise that the annual mean concentrations of particulates rate should not exceed 10 µg/m<sup>3</sup> for PM<sub>2.5</sub> and 20 µg/m<sup>3</sup> for PM<sub>10</sub>. World Health Organization report that there is about 2.4 million people die annually due to direct and indirect air pollution effect and about 1.5 million persons die of the indoor air pollution. Particulate matter (PM) contains an invisible solid and liquid particles with diameters of either less than 10µm<sup>8</sup> (PM<sub>10</sub>) or 2.5µm (PM<sub>2.5</sub>). They affect more people than any other pollutant and can penetrate the respiratory tract. PM<sub>2.5</sub>, being even smaller, can reach the most profound areas of the breathing apparatus such as the pulmonary alveoli [13]. Atkinson, R.W et al. [14] mentioned that the grown of delicate particulate matter (PM<sub>2.5</sub>) concentrations rate contributes to increasing the sensitivity to respiratory diseases like asthma and chronic obstructive pulmonary disease and lung cancer. Several laboratories and epidemiological studies mentioned that PM<sub>2.5</sub> raises the risk of respiratory morbidity and emergency visiting. Also, it increases aggravates chronic respiratory conditions. Therefore, the follow-up to the air quality will be considered as the most critical task of the

next generation. Despite all the significant progress in the development of air quality management systems over the past years, The European countries are still trying hard to achieve success in the air cleansing to be within acceptable standard levels that do not pose a threat to human life and the environment. Today, the particles (PM) and ground-level ozone (O<sub>3</sub>) are considered as the most problematic pollutants which are harmful to human health in Europe. Studies have shown that air pollution in Europe is the most significant risk factor in the overall health of human beings, and that causes premature death because it is causing a wide range of diseases [15] [16] [17] [18].

## 2.2 Air Pollution in Oman

The air pollutant is a severe case in areas with high population density and industrialized areas in Oman, especially in surrounding urban areas of Duqm and Sohar city. The Omani authority published laws aim to protect the environment and maintain the ecosystem the air pollution. Figure 3 presents a median rate of PM<sub>2.5</sub> ( $\mu\text{g}/\text{m}^3$ ) in the Arab countries with the highest rate. Moreover, it specifies strict laws to force companies and people to follow the standard level of prevention of environmental pollutants and gasses. They issue the laws such as RD 10-82, RD 114- in 2001, and the law RD 115- in 2001 for protecting the environment. Also, it issued the law MD 118- in 2004, which is an amendment to the environmental standards patterns for permanent emission resources [19]. Then it approved the law MD 159- in 2005 to control the marine discharges. Several monitoring stations have been created by the ministry of environment and Climate Affairs (MECA) to maintain and control the environmental data in the commercial zones and industrial zones. Besides, it creates permanent environment stations in the industrial zone at Al Rusail State and Sohar industrial zone. Abdul-Wahab et al. [20] Abdul-Wahab et al. recorded the effects of air pollution on the climatic abrasion of metals in Oman. The work shows that a high rate of corrosion is recorded in the Sohar zone, and the areas closest to the beach have higher concentricity of chlorides. Besides, they show that the industrial areas in Oman suffered from the highest carbonate levels. Abdalla et al. [21] conducted a study in areas surrounding the Sohar zone for examine the levels of SO<sub>2</sub>, TSP, dust, and PM<sub>10</sub>, and additional meteorology issues. Abdul-Wahab [22] performed a study to investigate the impact of environmental pollution issues on the plants from the use of natural gas liquid (OLNG) in the trains. The results show that different environmental pollutants were recorded like carbon monoxide (CO), Nitrogen oxides (NO<sub>x</sub>), methane (CH<sub>4</sub>), and non-methane hydrocarbons (NMHC).

Alwahaibi, A, and Zeka, A. [23] Ahmed performed a study to investigate the impacts of air condition on humans living nearby the industrial port zone. The results recorded several diseases like respiratory and allergic, heart disease in the four zones. The results were compared individually with the exposure control area to achieve the analytical results. The study shows a developing degree of skin infection in the three areas in the high exposure zone in the period 2007 to 2009.

Dinesh K. et al. [24] employed an unsupervised neural model based on Self-Organizing Feature Map (SOFM) to maintain and analyze the environmental data using real-time sensors and predefined static datasets acquired from monitoring stations. The neural model predicted the experimental data and simulated the behavior of the environmental system. Besides, feeding the results to be used in the reporting services and the alarming systems in interactive and dynamic management.

## 2.3 Data

The data used in this work is downloaded from the World Health Organization (WHO) [25], which contains the PM<sub>2.5</sub> and PM<sub>10</sub> data for worldwide countries. Besides, the annual reports of the Ministry of Environment and Climate Affairs (MECA) in Oman [19]. This paper focuses on discussing the impact of air pollution (especially PM<sub>2.5</sub>/PM<sub>10</sub>) in Arab countries in general and Oman in particular. Table 1 presents the annual median rate of PM in Gulf Council Countries (GCC) for the period from 1990 to 2017. The other weather factors like Ambient Temperature (TM), Relative Humidity (RH), Wind Speed (WS), Pressure (PRE), Wind Direction (WD), will be examined and analyzed for the sake of determining their effects on the human health and the relation with other factors.

Table 2 presents the standard limits of PM 2.5 based on the EPA Air Quality Index [26]. Figure 3 illustrates the median rate of PM<sub>2.5</sub> ( $\mu\text{g}/\text{m}^3$ ) in the countries with highest rate, which includes some countries in Arab region like Qatar, Egypt, Saudi Arabia, and Bahrain.

Table 1. The Annual Mean Rate of PM ( $\mu\text{G}/\text{M}^3$ ) in Gulf Council Countries (GCC). Source WHO [25]

Country Name	1990	1995	2000	2005	2010	2011	2012	2013	2014	2015	2016	2017
UAE	40	40	40	39	39	39	39	40	38	42	41	41
Bahrain	68	68	68	65	66	64	70	68	63	73	70	71
Qatar	92	90	84	85	84	81	89	89	79	94	88	91
KSA	71	73	79	76	82	82	86	84	76	97	84	88
Kuwait	61	60	61	60	63	63	64	63	56	65	61	61
Oman	40	40	40	40	38	39	41	41	38	43	42	41

Table 2. The Standard Limits of PM<sub>2.5</sub> (µG/M3) Based on Europe

Qualitative name	Pollutant (hourly) density in µg/m <sup>3</sup>	
Index	PM <sub>2.5</sub>	AQI indicator
Good	0–12	1
Moderate	12.1–35.4	2
Unhealthy for Sensitive	35.5–55.4	3
Unhealthy for all	55.5–150.4	4
Very Unhealthy	150.5–250.4	5
Hazardous	250.5–500	6

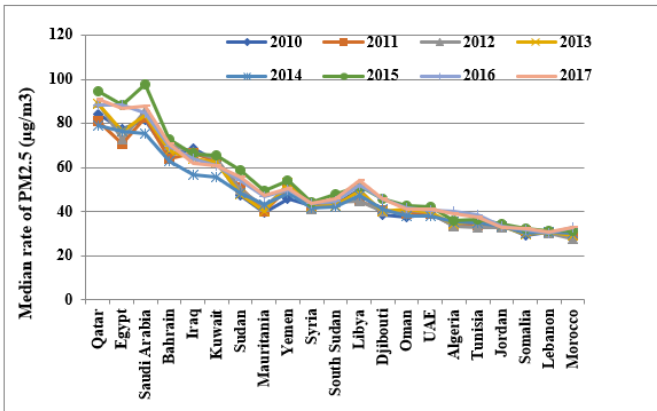


Fig 3. The median rate of PM (µg/m3) in the countries with highest rate

### 3 Research Methodology

This research paper implemented a quantitative research methodology that will analysis the historical data for determine the relationship between the input and output factors. A hybrid neural network and mathematical approaches will be utilized for examining and determining the effect of particulate (PM<sub>2.5</sub> and PM<sub>10</sub>) on human health in Oman. Besides, we will try to obtained answers for the following research question:

- 1) What is the impact of particulate (PM<sub>2.5</sub> and PM<sub>10</sub>) on human health in Oman?
- 2) What is correlation rate of short-term particulate (PM<sub>2.5</sub> and PM<sub>10</sub>) with human health?
- 3) What is correlation rate of long-term particulate (PM<sub>2.5</sub> and PM<sub>10</sub>) with human health?
- 4) What is the optimum particulate conditions for reducing the effect rate of particulate on human health?

### 4 Neural Networks Modeling

Artificial Neural Networks (ANN) is a novel paradigm for computing complex models, which simulate the biological activities of the human brain. A neural network is a powerful tool able to learning and propagation of both linear and nonlinear data. It is implemented in various applications such as prediction, filtering, and classification

data. ANN has several properties like the ability to learn and train, parallelism computation, uniformity of data, and ability of generalization [17]. The ANN topology determines the number of input, output, and hidden layers. The processing unit is called Neuron, which accepts data sets as inputs and composing an individual output. The input layer receives the data set that contains a set of variables. Moreover, the output layer generates a set of data that could be reused as input again. Self-Organizing Map (SOM) is typically unsupervised learning strategies that rely on the idea of Organizing feature maps. The input is high-dimensional features, and the output will be a systematized two-dimensional feature map.

The central concept in the SOM learning method is that the processing winner node and its neighborhoods will be clustered to closer input data space. The Hebbian rule is used in the modification of weights. Any modifications in winner neuron will affect the neighboring of this Neuron. Therefore, the adjustment of weights must be implemented on the Neuron and its neighbors. The training of SOM involves mapping up the higher dimensional input space into two-dimensional feature maps. Figure 4 illustrates a self-organizing feature map neural network architecture.

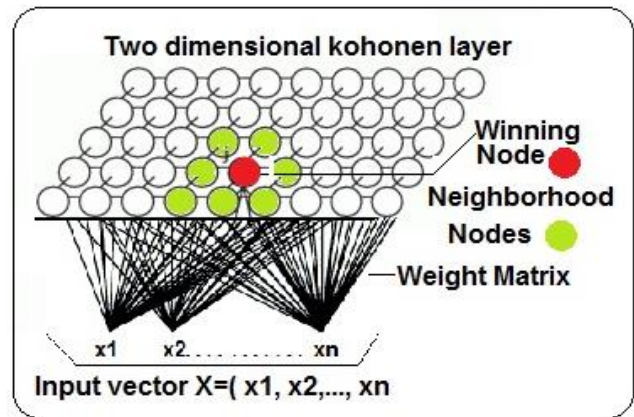


Fig 4. Self-Organizing Map Architecture

For the purpose generalization of the network for unseen samples, the ‘match’ of training sets is used. Before using the neural network, a preprocessing is implemented to encode the input text into a suitable form. The ANN needs three categories of data. First, training data sets to use to train the network. And the cross validation data sets to adjust the weights of network. Lastly, the test data sets for testing the efficiency of network.

The comparison of cross-validation data sets with training data sets is helps to determine the error in a test data sets. This work includes a SOM approach, which is



implemented and composed using the NeuroSolution software package. The experiment involves 500 data sets that classified into 60% training data, 20% testing data, and 20% cross-validation datasets. The experiment determines the maximum number of epochs to 1000. The SOM network consists of eight input variables (the data year 2010-2017), one hidden layer based on momentum function with learning rate =0.7, step size=1. And one output variable (QAI). The matrix of the neighborhood shape employs a full square-Kohonen method with five rows and five columns. The starting radius is two, and the final radius is zero. The TanhAxon transfer function is deployed in the hidden and output layers. The maximum number of unsupervised learning epochs is 100.

Several methods used to evaluate the performance and accuracy of predicted models. The “coefficient of determination” (R2) is a major approach that used to evaluate the validity of the predictive results compared to experimental results. It is defined as in equation (1).

$$R^2 = 1 - \frac{\sum_i^n (y_i - f_i)^2}{\sum_i^n (y_i - \bar{y})^2} \quad (1)$$

where, y is the experimental data and fi is the predicted data. In addition,  $\bar{y}$  is the mean of experimental data and n is the number of data.

In addition, some other methods are used such as the Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), and “Mean Square Error” (MSE) that are computed as in equations (2), (3) and (4), respectively.

$$NMSE(f) = \frac{100}{N\sigma_y^2} \sum_{i=1}^N (y_i - f_i)^2, \sigma \text{ is the standard deviation}(2)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |f_i - y_i| \quad (3)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2 \quad (4)$$

## 5 Results and Discussion

This section will review and analyze the results of this work, which is classified into two main sections. First, it discusses the statistical and mathematical results. Moreover, the second section will analyze the neural network results and their impact. The comparison of the two approaches will be examined and verified based on the standard evaluation methods.

Descriptive statistics data serve to interpret large amounts of data sensibly. Each factor in descriptive statistics is used to reduce lots of data into a small summary. Table 3

depicts a summary of descriptive statistics data, which include maximum value, minimum value, mean, and standard deviation. The observations are (18 Arab countries). The maximum value is 58.9, which indicates that all the Arab countries are not in a hazardous zone. The standard deviation recorded is between 12 and 14, which means that all Arab countries are in the good and moderate index of pollution level. The median range is between 18 and 22, which is near the range of Standard deviation values, which means most PM 2.5 (µg/m3) emission populations have happened in the first portion of the curve in the good and moderate AQI indicator.

Table 3. Summary of Descriptive Statistics Data of PM2.5 (µG/M3) of Arab Countries

Statistic	2010	2011	2012	2013	2014	2015	2016	2017
No. of observations	18	18	18	18	18	18	18	18
Minimum	7.85	8.09	7.33	7.17	6.94	6.92	6.60	6.48
Maximum	55.84	56.38	51.64	52.44	48.14	58.90	54.14	55.37
1st Quartile	15.65	16.45	16.17	15.42	14.95	14.83	14.39	14.49
Median	22.42	23.02	21.33	21.03	19.75	19.78	18.93	18.73
3rd Quartile	31.54	32.10	32.28	31.92	31.03	33.62	31.97	32.34
Mean	25.86	26.31	25.33	24.87	24.22	25.68	23.98	24.14
Variance (n-1)	166.51	171.13	162.56	161.08	158.66	213.68	177.21	186.81
Standard deviation (n-1)	12.90	13.08	12.75	12.69	12.59	14.61	13.31	13.66

Figure 5 illustrates the rate of annual median PM 2.5 (µg/m3) rate in the Gulf council countries in the period of 1990 to 2017. The figure presents the historical data of PM 2.5 (µg/m3) rate of gulf council countries in line with the standard limits of PM 2.5 (µg/m3) based on the EPA Air Quality Index. The figure clearly shows that all the Gulf council countries are far from the hazardous area of environmental pollution. Most are located in the moderate zones such as Oman and Kuwait, while Saudi Arabia, Bahrain, the United Arab Emirates, and Qatar are within the unhealthy area of some people sensitive to different types of gases and molecular pollutants. The highest zone are Saudi Arabia and Qatar, with an average of 90 (µg/m3), and Bahrain is located in the second-highest place with an average of 80 (µg/m3).

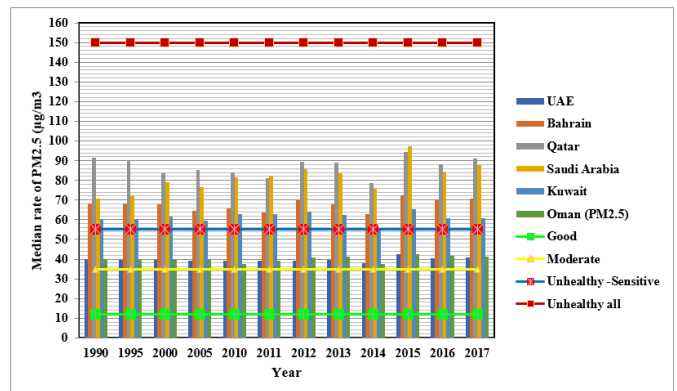


Fig 5. PM 2.5 rate of Gulf council countries in the period of 1990 to 2017

Figure 6 presents the predicted average rate of PM<sub>2.5</sub> (µg/m<sup>3</sup>) of Arab countries from 2010 to 2017 based on two mathematical regression models (Linear & Nonlinear) that are presented in Table 4. It shows that the Saudi Arabia, Algeria, and Tunisia are the most Arab countries zones suffer from the high emission PM<sub>2.5</sub> (µg/m<sup>3</sup>) rate. Therefore, proper actions should be taken to manage the source of air pollution like transportation, power generation from Oil, and to increase the use of renewable energy sources. Figure 5 illustrates that the nonlinear regression model fits the experimental data closely.

It achieves a coefficient of determination (R<sup>2</sup>) value of 0.9394 and mean square error (MSE) rate of 0.0209, and root mean square error (RMSE) value of 0.1447. However, the Linear regression models achieve fewer results of R<sup>2</sup>, MSE, RMSE (0.7604, 0.0673, 0.2595), respectively.

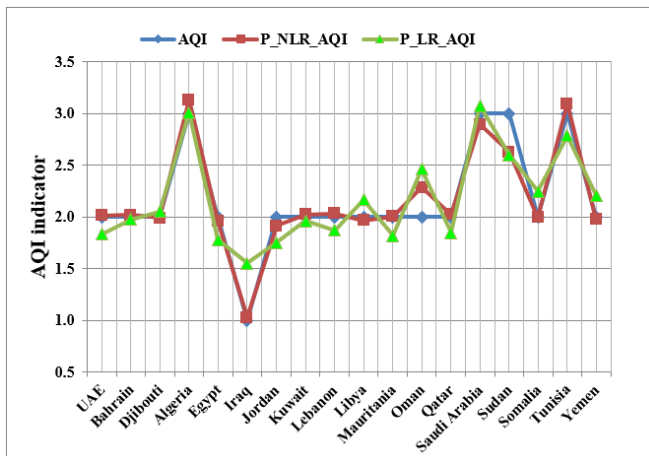


Fig 6. Predicated PM 2.5 (µg/m<sup>3</sup>) rate of Arab countries from 1990 to 2017 Based Linear and Non-Linear regression models

Table 4. The Mathematical Equations for Predicting Future Levels & Goodness Factor Measurement

Model	Predicted Equation	R <sup>2</sup>	MSE	RMSE
Nonlinear Regression	$P\_NLR\_AQI = -2.46688 + 0.75810 \cdot AV - 0.04533 \cdot AV^2 + 0.00112 \cdot AV^3 - 9.45045E-6 \cdot AV^4$	0.9394	0.0209	0.1447
Linear Regression	$P\_LR\_AQI = 1.30661 + 0.03433 \cdot AV$	0.7604	0.0673	0.2595

The SOM network is implemented and designed using the NeuroSolution package. NeuroSolution provides different factors for measuring the goodness rate of predicting future data such as NMSE MSE and MAE as defined in equations 2, 3, 4, respectively. Table 5 presents the obtained results of the neural model (SOM) that achieve MSE value of 0.0064, correlation rate (R) value of 0.994, NMSE value of 0.01392, and MAE value of

0.0467. Figure 7 shows the training curve of three tests with 1000 epochs for the sake of getting accurate results.

The figure presents a smooth training form the data from the epoch 100 with an interesting value of average MSE compared with standard deviation boundaries for 3 tests.

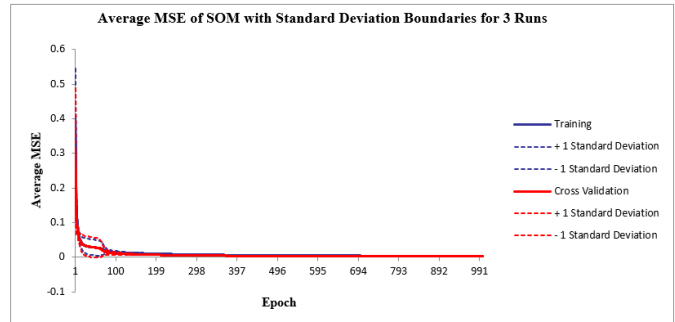


Fig 7. Average MSE of SOM with Standard Deviation Boundaries for 3 Runs

The results show close fits of experimental data using the predicting neural model with a Correlation rate of 99%. Figure 8 depicts the results of predicted data compared to experimental results, which shows close fits between the two data sets. This means the SOM model trained and generalized the behavior of experimental data in a fast, accurate, and low-cost model that can be used easily to generate the needed data in the future for any period.

Table 5. The SOM Model for Predicting Future Levels & Goodness Factor Measurement

	MSE	Correlation rate (R)	NMSE	MAE
SOM Neural network	0.0064	0.994	0.01392	0.0467

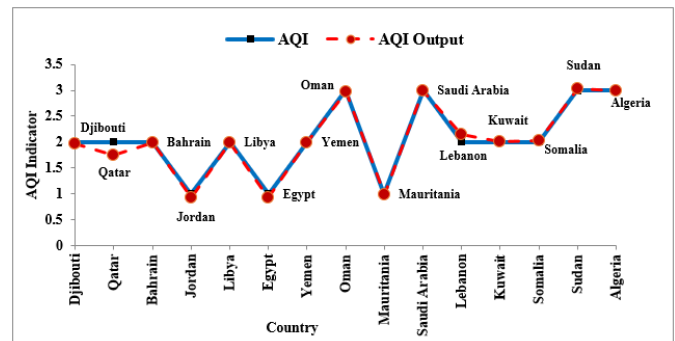


Fig 8. Predicated PM (µg/m<sup>3</sup>) rate of Arab countries from 1990 to 2017 using SOM network model (data from Table 1)

## 6 Conclusion and Future Work

The paper proposed a comparative study to identify the impact of air pollutants, including particulate matter (PM) levels on human health in the Arab countries in general and Oman in particular. As well as, the paper suggested

three mathematical models that predict the values of pollutants in the future in a fast, cheap, and safe method.

The first mathematical model is inexpensive and easy to apply a linear regression prediction model with satisfactory results. However, the Linear regression models achieve fewer results of  $R^2$ , MSE, RMSE (0.7604, 0.0673, 0.2595), respectively. The results were examined and verified using several methods based on equations 1, 2, 3, and 4. The second mathematical model, a non-linear regression polynomial prediction model, obtained excellent results that predicted pollution data significantly compared to laboratory data. It achieves a coefficient of determination ( $R^2$ ) value of 0.9394 and mean square error (MSE) rate of 0.0209, and root mean square error (RMSE) value of 0.1447. These results were also verified by the mathematical methods mentioned in equations 1, 2, 3, and 4. The third model is using the Neural SOM model, which obtained results of the neural model (SOM) that achieve MSE value of 0.0064, correlation rate (R) value of 0.994, NMSE value of 0.01392, and MAE value of 0.0467. The results showed an exact match between the actual values and the value generated using the Neural SOM model.

The research methodology involves several steps, including studying and analyzing previous work, obtaining data, and finding mathematical models that can simulate the real data. Finally, apply the comparative study to get answers to research questions and future recommendations. The work is continuing as a study project for a Ph.D. degree, so this paper answered about system analysis, conduct a survey of previous work, data generation, and proposing mathematical models. As well as answer the research questions of studying the impact of pollutants in the short and long term. The work proved that the Arab countries in the region of (good and moderate based AQI indicator) and did not reach the degree of danger of pollutants therefore, as a future work will complete the stages of research, including the study and analysis of the impact of particulate matter on human health accurately and the relationship of pollutants with various environmental changes such as air-speed, pressure, and humidity. Besides, it will deploy the sensitivity analysis to determine the critical impact of each particulate matter that could help to reduce the emission rate. More neural techniques could be performed, such as multilayer perceptron, recurrent neural models, and fuzzy control models.

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