Rouzbeh Jafari Tofighi FORCASTING MEGACITY POLLUTANTS USING CLASSICS AND EMOTIONAL ARTIFICIAL NEURAL NETWORKS Master Thises 2021

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FORCASTING MEGACITY POLLUTANTS USING CLASSICS AND EMOTIONAL ARTIFICIAL NEURAL NETWORKS

M.Sc. THESIS

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Approval

We certify that we have read the thesis submitted by Rouzbeh Jafari Tofighi titled **"FORCASTING MEGACITY POLLUTANTS USING CLASSICS AND EMOTIONAL ARTIFICIAL NEURAL NETWORKS"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Educational Sciences.

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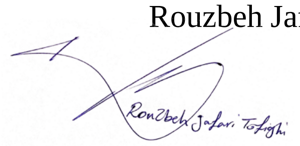
Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Rouzbeh Jafari Tofighi



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Abstract

FORCASTING MEGACITY POLLUTANTS USING CLASSICS AND EMOTIONAL ARTIFICIAL NEURAL NETWORKS

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Modeling of environmental pollutants is one of the essential necessities for air quality monitoring which somewhat preventive actions can be taken in the future by the use of outcomes of the modeling. If a reliable model can be presented for predicting the upcoming situation of pollutants in a city like London, with a good cognition from the trend of pollutants, appropriate solutions with high efficiency can be designed for each of pollutants. By and large, air pollution in a city like London has 3 characteristics: 1.some source of pollution or pollutants which is harmful to the health of humans, have entered in atmosphere. 2. Dissemination has taken place in the atmosphere by the way of a broadcasting process in which temperature and humidity have an active role in this occurrence. 3. Potential for contamination, which depends on the environment, geographical location, and topography. For modeling air pollution for the city of London, in terms of modeling, first, the meteorological and pollutant data should be gathered from the Meteorological and Environmental Organization, then after determining the effective inputs, the prediction of pollutants will take place. The description of data uses can refer to the kind of data, utilized for designing a plan for predicting pollutants. Four types of impressive pollutants such as Nitrogen dioxide, Sulfur dioxide; Particulate matter 10, and Particulate matter 2.5 are used. Measured in Micrograms per Cubic Meter of Air (ug/m3) and the data has used, measured by time of day per month between 2010 and 2019. 75 percent of whole data have been used for calibration and 25 percent for validation. The mentioned pollutants have been forecasted with three types of modeling systems, which are Feedforward Neural Network (FFNN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Emotional Artificial Neural Network (EANN). Having said that, by the ratio of DC verification

and RMSE value, the performance of EANN had better rather than FFNN ANFIS. So that, the pollutant of NO2 based on DC verification and RMSE value, FFNN modeling performed 19% better than ANFIS. EANN also performed 10% and 28% better than FFNN and ANFIS, respectively. In the case of PM2.5 pollutants, based on DC validation and RMSE value, FFNN modeling performed 13% better than ANFIS. EANN also performed 8% and 21% better than FFNN and ANFIS, respectively. In the case of PM10 pollutants, based on DC validation and RMSE value, FFNN modeling performed 9% better than ANFIS. EANN also performed 18% and 27% better than FFNN and ANFIS, respectively. In the case of SO2 pollutants, based on DC validation and RMSE value, FFNN modeling performed 8% better than ANFIS. EANN also performed 14% and 22% better than FFNN and ANFIS, respectively.

The FFNN model is a good model for air pollutants due to its artificial intelligence structure, which also has neurons. The ANFIS model is a combined model of fuzzy modeling and artificial intelligence that can improve the results, but in the present study, the reason for the better performance of FFNN than ANFIS can be stated in the high number of layers of the ANFIS model. The inputs are also very high, with a small error RMSE at the beginning, a high final nonlinear error was obtained. Also, the reason for the superiority of EANN over other models can be explained by the addition of hormone to the structure along with the neurons in it.

Keywords: Air pollution, Feedforward Neural Network, Adaptive Neuro Fuzzy Inference System, Emotional Artificial Neural Network, London

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CHAPTER I

Introduction

In this chapter, some general information is presented. First, an introduction regarding air pollution and the modeling is about to be discussed. So that, somewhat questions and hypotheses have appeared to identify the path of research. At the end, an introduction of the structure of the thesis has presented.

Problem Description

Air pollution is one of the vital problems in the human society. According to the World Health Organization, 9 out of 10 people breathe polluted air and up to 7 million people are dying form air pollution annually (WHO,2008). Urban expansion, urban development, population growth, development of industrial activities and increasing consumption of fossil fuels, lack of efficient public transportation system, low fuel quality, and traffic congestion caused the intensive volume of incompatible pollutants evacuated into the air with a normal mechanism (Jain and Khare, 2010). Air pollution is one of the troubles in the industrial and mega cities in the world and it threaten health of the humans who are living there seriously. Air pollution can have long-term and short-term impacts on the health of humans. Normally, the effect of air pollution on humans is mainly on the eyes and breathing Organ, in which in the short term, it causes irritation and irritation of the eyes, nose, throat, and lungs, and in the long-term, it causes cardiovascular diseases, asthma, bronchitis, and various respiratory allergies in humans (Anderson, 2009). The previous studies indicated, that there is a close bond between the pollutants like Carbon dioxide, Nitrogen dioxide, PM 10 and respiratory and cardiac mortality, pulmonary infections, and acute diseases that need intensive care (Liang et al., 2009).

Modeling of environmental pollutants is one of the basic needs in the field of air quality monitoring which with the use of the results; preventive measures can be taken to improve future conditions. If a reliable model can be provided to predict the future state of pollutants in the city air, with a more accurate knowledge of their future trends, a high-efficiency solution can be designed to deal with each of these contaminants. In this way, in case of lack of necessary attention to this issue, it will lead to intensive costs. Studies on the modeling and prediction of pollutants can be divided into four general methods: 1. Artificial intelligence method (Bodaghpour, Charkestani, 2011; Ibarra-Berastegi et al., 2008). 2. Prediction method with linear regression (Pires et al., 2008) 3. Prediction method with autoregressive models (Ibrahim et al., 2009; Marzuki et al., 2011; Kumar and Ridder, 2010) 4. Prediction method with combined models (Diaz-Robles et al., 2008, Siew et al., 2008) which will be reviewed in the part of inspection of sources.

Research objective and research question

This study has aimed to come up with a particular model for predicting the density of pollutants like PM10, PM 2.5, NO2, and SO2 by the use of Feedforward Neural Network (FFNN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Emotional Artificial Neural Network (EANN). Modeling of environmental pollutants is one of the essential requirements in the field of air quality monitoring which by using the results; we can attempt to implement a preventive action to improve future conditions. In terms of modeling, first, the pollutants data and meteorological has been gathered from the Meteorological and Environmental Organization, then after determining the effective inputs, the prediction of pollutants have been taken place.

Research question

This research seeks to answer the following questions.

1. What parameters affect the prediction of air pollutants in London?

2. How much is the correlation of the input data for a more accurate prediction?

3. What is the best model among the selected methods for predicting pollutants?

4. How much will the quality of pollutants for London in the future?

The research objective shall be closely followed in order to address these questions. These research questions will be used to create interview questions for this study.

Significance and importance of the study

Air pollution has become a serious environmental concern in many countries as a result of the rapid expansion of industrialisation and urbanization in recent decades. (Xian et al., 2019) According to research, power generation, industry, transportation, agriculture, and residential activities are the principal contributors of urban air pollution. Air pollution can have both long-term and short-term effects on human health. The eyes and respiratory system have been the primary targets of air pollution, causing irritation of the eyes, nose, throat, and lungs in the short term. Humans, on the other hand, are affected by cardiovascular diseases, asthma, bronchitis, and a range of respiratory allergies (Anderson, 2009). Several review papers and meta-analyses have found that air pollution has a direct impact on respiratory responses and disorders (Guan et al, 2016).

Air pollution has been a very complicated process, which is depending on several factors such as topography, Climate, Population, Transportation Network, Industry and so on. Therefore, it is very difficult to predict such data with non-linear dynamics. Having said that, should determine the circumstance of dispersion and emission of pollutants on the atmosphere. If it is considering several factors for making a model, there are some sudden factors like increasing the production of cars, architecture, urban Development that cause to being incorrect modeling and prediction so a method is needed because of the uncertainty in most spatial entities that should have an ability of learning and Inference with considering the uncertainty. In terms of dealing with these challenges, human associations utilize models based on Artificial Intelligence, which is able to extract patterns in data in recent years. Nevertheless, the ANN is not comparative with Natural Nervous Systems but it has somewhat properties like Pattern separation, Robotics, Control that is the cause of being wealthy rather than Natural Nervous Systems. These properties can be the ability of learning, distributed processing, generalizability. The networks have created from an input layer, an output layer and one or some middle layers that are called hidden layers *(*Artificial_neural_network @ en.wikipedia.org, n.d.).

Thesis limitations

1. It is assumed that the quantity of pollutants is predictable with a specific method with complicated ways like FFNN and ANFIS.

2. It is assumed, with constant emission source of pollutants, the amount of emission will reserve with the previous pattern.

3. The data have gotten from the meteorological office and air quality office is valid enough.

Thesis structure

The structure of the present Thesis will be as follows:

In the first chapter, the problem, questions, and hypotheses of the research were stated.

In the second chapter, first the theoretical foundations and then the background of the research has given.

In the third chapter, first, the research method and then the study area will be introduced.

In the fourth chapter, the results and analyzes of the performed models are presented. The results include various tables, pictures, and diagrams. The analyzes also based on the results, and their comparison is has obtained with each other.

In the fifth chapter, the general conclusion of the prediction of air pollutants will be done using Classical and Emotional Artificial Neural Networks in London. Then a summary will be made and the proposed studies will be introduced.

CHAPTER II
Literature Review

This chapter consists of two parts. In the first part, the theoretical and conceptual foundations of the research are described and the basic scientific concepts and documents related to the present study are given. The purpose of expressing the theoretical and conceptual foundations of the study is to explain the subject. In the second part, scientific studies and researches are presented which is related to the research topic. The purpose of reviewing the studies is to search for different sources of information in order to master the various dimensions of the research topic. To review the studies conducted and work on current research.

Theoretical Foundations

Theoretical foundations of the research, including information about atmosphere and air pollution caused by air pollutants including monoxide, air pollution indicators and standards, PM10, Carbon dioxide, Nitrogen dioxide, Sulfur, particulate matter history of air pollution in England and the world, concentration of pollutants, climatic parameters related to pollution air includes humidity, temperature; have been discussed separately and in more detail.

The atmosphere is a cover that holds life on the Earth against the deadly environment of cosmic space. The protective function of the atmosphere is very important because it absorbs a lot of cosmic radiation from space and protects creatures from the destructive effects of this radiation. The atmosphere has divided into different layers thermally, which are from bottom to top, respectively:

I) Troposphere: It contains the atmosphere and hydrosphere in which life exists. It is the closest layer to the surface of earth in the atmosphere. This layer has a thickness of about 12 km in medium latitudes. Its main features are decreasing temperature with increasing altitude.

II) Stratosphere: This layer extends about 50 km above the ground. In this layer, the temperature has an upward trend with increasing altitude. The reason for this increase is the presence of ozone. Ozone absorbs energy in the form of ultraviolet light and is a cause of the increase in temperature. Its importance is due to the presence of ozone in this layer, which is able to absorb very much of the sun's ultraviolet rays. Most parts of the Ozone layer exists in this layer.

III) Mesosphere: This layer continues to an altitude of about 80 km above the ground. The lower part is warmer because it is adjacent to the stratosphere and is affected by its temperature. With increasing altitude, its temperature decreases, which is due to a decrease in the amount of radiation absorbing compounds, especially ozone.

IV) Thermosphere or ionosphere: This layer starts from about 80 km above the ground and continues to an average altitude of between 500 and 900 km depending on different latitudes, with an increase in altitude, the temperature will be enhanced. This is due to the absorption of high-energy radiation with a wavelength of less than 200 nm by the chemical species in this layer.

V) Exosphere: It is the last layer of the atmosphere that starts from an altitude of 500 to 900 km and continues until absolute vacuum. In this layer, gaseous molecules are aroused by receiving solar radiation so because of that, it is called the exosphere (Buchholz, Y. 2017).

Anything that changes the natural quality of the air is called Air Pollution. In other words, air pollution occurs by somewhat factors that have a direct impact on human health, plants, animals and even buildings. In other words, in the air we breathe, there are certain gaseous compounds that change in these compounds cause pollution. These gaseous compounds include Nitrogen, Oxygen, Carbon dioxide, and so on. Another definition of air pollution states that: every changes in the natural quality of the air is called Air Pollution.

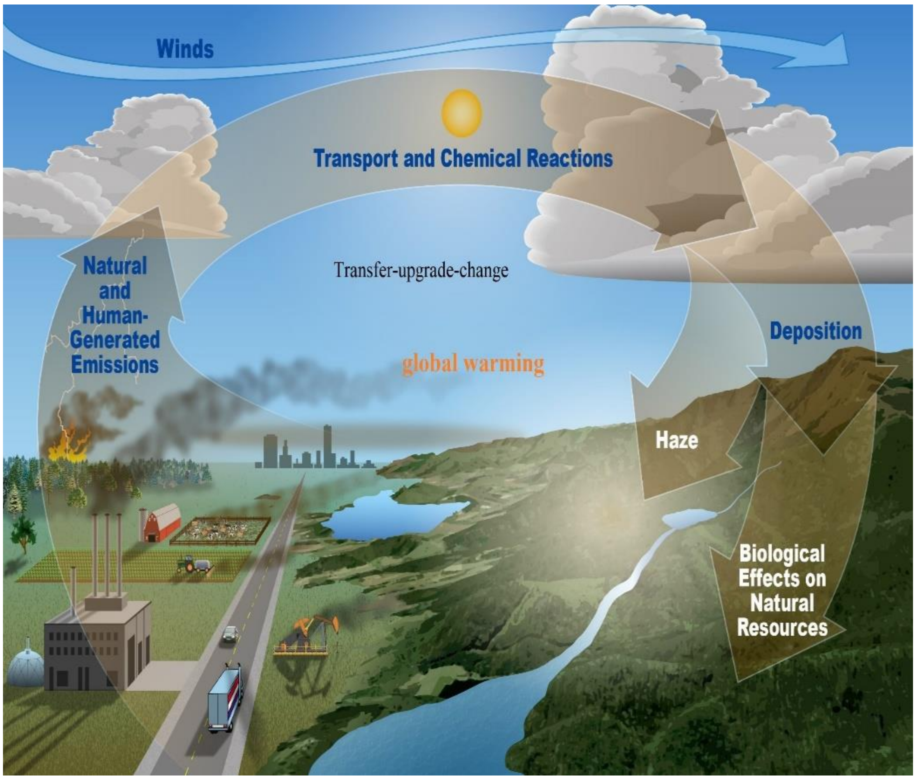
According to the American standard, the Air Pollution is defined as follows: If one or more high concentrations of pollutants are in the air for a period of time that harms humans, plants and animals or reduces the comfort and tranquility of life, it is called polluted air (Jung, M., et al, 2019).

In general, it can be stated that; Air pollution means that air mixes with gases, liquids and solids that reduce air quality. Polluted air is a phenomenon that is produced by combining or mixing air with certain substances or particles over a period. In addition, if it persists, it causes diseases and disorders for humans, animals and plants (Eslami, A., & Ghasemi, S. M. 2019).

Figure 1 shows a schematic of the air pollution process. Some sources enter pollutants into the atmosphere and these substances, addition to move and evaporate in the atmosphere, also undergo chemical and physical changes. Finally, due to exposure to the acceptor, some damages will be occurred to the health of materials and other components of the environment.

Figure 1

Air Pollution Process



The air pollutants that have studied and modeled in the present study are: Particulate Matter 10 **(**PM10), Particulate Matter 2.5 (PM 2.5), Nitrogen Dioxide (NO2), and Sulfur dioxide (SO2) in which the characteristics of each of them are mentioned below.

Seven types of oxides have been identified for nitrogen until now, including NO, NO2, NO3, N2O3, N2O4, N2O5. Nevertheless, usually only three of them have found in the atmosphere, which are:

Nitrous oxide (N2O) is a colorless, non-flammable, non-toxic gas with a relatively good odor.

Nitric oxide (NO) is a colorless, non-flammable, odorless and toxic gas.

Nitrogen Dioxide (NO2) is a reddish-brown, non-flammable, odorless, and highly suffocating gas (Burns et al, 2020).

The sources of nitrogen oxides are 80% natural and 20% artificial, and as a result, the share of natural sources in the production of this pollutant is higher than artificial sources. Nitrous oxide is not a pollutant but can affect global warming and ozone destruction. Fermentation of bacteria usually leads to the production of nitrous oxide. Combustion is the main source of Nitrogen oxide production artificially. Nitrogen and oxygen react during combustion at high temperatures, leading to the formation of nitrous oxide and nitrogen dioxide (Burns, et al, (2020)). The relative amount of nitrous oxide and nitrogen dioxide produced depends on the combustion temperature and the ratio of nitrogen to available oxygen. Among all the types of available oxides, almost all the oxides of Nitrogen that are dispersed in the air are Nitrogen oxide. This gas has no known effect on human health with concentrations in the atmosphere. However, when oxidized, nitrogen oxide to nitrogen dioxide and combined with hydrocarbons in the presence of sunlight, chemical fog is formed. Besides, nitrogen dioxide in the combination with radical hydroxyl leads to the production of nitric acid, which eventually falls in the form of acid rain on the ground(Daigle, 2010).

Other sources of nitrogen oxides include motor vehicles, power plants (fossil fuels), natural gas burning, oil-fired furnaces, electrical discharges into the atmosphere, and chemical plants such as nitric acid can be mentioned (Burns et al, 2020). Nitrogen oxide pollution in the air, despite the presence of nitrous oxide in the atmosphere, have usually considered in terms of nitrogen dioxide and nitrous oxide. The reasons for this action are:

I) Nitrogen oxide and nitrogen dioxide are toxic, while nitrous oxide is not.

II) Nitric oxide and nitrogen dioxide contribute to the photochemical reactions of the atmosphere.

III) Nitric oxide and nitrogen dioxide are major synthetic sources. The symbol NOX is often used for a set of nitrogen oxides and nitrogen dioxide involved in air pollution (Daigle, 2010).

Almost all nitrogen oxides and nitrogen dioxide from artificial sources have produced by atmospheric oxidation of nitrogen during high-temperature combustion. Nitrogen and oxygen create nitrous oxide, which the react with nitrogen oxide, oxygen and nitrogen dioxide will be achieved (Burns, J. et al. E. A. 2020). Nitrogen oxides, including nitrogen dioxide and nitrous oxide, can be potentially hazardous to human health. Increasing the concentration of these contaminants may cause consequences such as respiratory problems, eye and throat irritation, nerve sicknesses, or inflammation in the lung tissue. In addition, the presence of nitrogen oxides in the atmosphere can damage plants and affect the structures and color of objects(Dalmiya et al, 2012).

The maximum amount of Sulfur oxide exposes in the atmosphere. Sulfur dioxide is a colorless, non-flammable gas. The natural origin of sulfur oxides is SH2, which is existed in the atmosphere and is produced from spoilage of organic matter. The emission of artificial sulfur oxide is mainly due to the combustion of coal. Combustion of petroleum fuel and melting of sulfide rock has a small but very important role in the release of sulfur dioxide into the atmosphere. Industrial processes can be a major source of sulfur dioxide emissions. More than 80 percent of Sulfur oxides are produced by a human, which is due to the combustion of fossil fuels from fixed sources of pollution. 85 percent of this amount belongs to the Electric powerhouse and just 2 percent for the cars. Also, among the industries, oil refineries and copper smelters are playing an important role in the production of sulfur oxides. Most of the effects of sulfur dioxide on human health relate to direct respiratory disorders. Most deaths from air pollution often relate to the adverse effects of particulate matter along with sulfur oxides (Maleki, et all, 2019).

Particles smaller than 10 micrometers are called PM10 and in this research, will be among the pollutants. Also, it needs to be attention that particles smaller than 2.5 are PM 2.5 and it is one of the hazardous ones in the field of Human health issues that even the human respiratory system is not able to filter this pollutant, unlike PM 10 pollutants.

Particulate matter is a type of air pollution that includes any type of substance floating in the air. These floating material particles include dust, smoke, and micron particles. The content of these particles varies from coarse sands to various metals, depending on the geography of the place and the specifications of the soils (Gu, 2018).

The source of increasing fine dusts in the air is various and may be of natural or artificial origin. Human activities such as agriculture, volcanic eruption, desertification, hurricanes and the like are included (Xu, 2019).

Natural Particulate matter defines as penetrating the soil surface particles into air which is blowing and horizontal and vertical transmission. Having said that, it causes an decreasing in vision (Wang, 2017).

Studies show that air pollution caused by fine dust is a factor in not achieving sustainable urban development. The phenomenon of fine dust is one of the climatic climate disasters, the occurrence of which causes damage to the environment and the occurrence or exacerbation of respiratory and heart diseases, air and ground traffic, tourism, agriculture, etc. In addition to the intensity, wind speed and dryness of soil particles, the frequency of dust occurrence in an area also depends on the size and diameter of the particles. Vegetation also depends on the intensity, wind speed and dryness of soil particles and the size and diameter of the particles. Vegetation have played an active role in intensity of dust occurrence. Plant density and structure are the two main controlling factors in the occurrence and frequency of dust storms (Sanchez et al., 2020).

The most important factors and elements that cause fine dust are summarized as follows (Sanchez et al., 2020).

I) Extensive desert bed or desert

II) Topographic shape in the direction of favorable winds to channel flows

III) Sufficient suspended bed load

IV) Sudden strong winds

V) Drying of aquifers and rivers by human intervention or the natural cycle of the climate

VI) Intense erosion

The effects and consequences of fine dust are:

Effects of the causative agent of the disease:

I) effect on mental health

II) exacerbation of asthma by fine dust

III) effect of fine dust on the eyes

IV) effect of fine dust on the lungs

Effects of declining quality of life factors:

I) Effect of particulate matter on tourism

II) Effect of particulate matter on security

III) Particulate matter and deforestation

IV) Effect on agricultural production

V) Effect on water resources

Indicators and standards of air pollution

Air quality standards are based on two types by the US Environmental Protection Agency: primary and secondary standards. According to the definition of basic standards, those are the standards that must be observed to maintain the general health of society (regardless of economic and technological issues). These standards have attached in the Table 2.1, which is essential for the health of sensitive people, especially the elderly, respiratory patients and children. Secondary air quality standards have wider dimensions than the primary standards, so that these standards consider the protection of resources and public comfort (Zeng et al, 2020).

Table 1.

Preliminary Air Pollution Standards (Based on Global Health WHO)

Pollutant	Primary/ Secondary	Averaging Time	Level	Form
NO2	Primary	1 hour	100 ppb	Averaged over three years, the 98th percentile of 1-hour daily maximum concentrations
	Primary and Secondary	1 year	53 ppb	Annual Mean
PM 2.5	Primary	1 year	12.0 μg/m^3	a three-year average of the yearly mean
	Secondary	1 year	15.0 μg/m^3	a three-year average of the yearly mean
	Primary and Secondary	24 hour	35 μg/m^3	Averaged over three years, 98th percentile
PM 10	Primary and Secondary	24 hour	150 μg/m^3	Not to be surpassed more than once every three years on average.
SO2	Primary	1 hour	75 ppb	Averaged over three years, the 99th percentile of 1-hour daily maximum concentrations
	Secondary	3 hours	0.5 ppm	This limit should not be exceeded more than once a year.

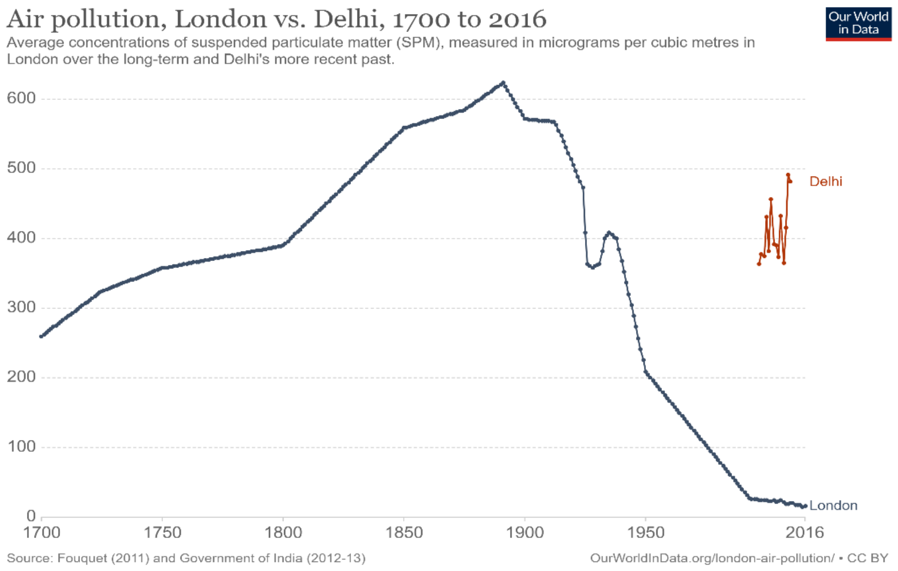
History of air pollution in England and The world

The phenomenon of air pollution has a long history, especially in metropolitan areas. As historians write, in cities such as medieval London, the evidence of overuse of coal that caused air pollution has been in 16th century in the written form. In Britain, during the Industrial Revolution and the rise of coal-fired industries, along with coal fuel used in homes, pollution levels sometimes rose sharply. When fog is created, these pollutants showed themselves in the form of thick smoke. This phenomenon led to the closure of cities and increased mortality. Gradually, the effect of these phenomena on buildings and agricultural products became clear. In 1875, the first attempts were made to legislate to reduce pollutants and improve the health of people in urban areas (Malakooti, 2010).

Cities in most high-income nations have generally downward levels of neighborhood discuss contamination compared to cities in more quickly creating ’emerging economies’. This, in any case, has not continuously been the case. National discuss contamination patterns frequently take after the natural Kuznets bend (EKC). The EKC gives a theory of the connection between natural debasement and financial advancement: in this case, discuss contamination at first declines with the onset of mechanical development, but at that point crests at a certain arrange of financial advancement, and from at that point on contamination levels start to decay with expanded advancement. Numerous high-income countries are presently at the late organize of this bend, with comparably moo contamination levels. In the meantime, creating countries span different stages of the growth-to-peak stage. In figure 2.1 have already composed the related phenomenon in connection to sulfur dioxide (SO2) outflows here on the Our World In Data (Marlier et al, 2016).

Figure 2.

Air pollution, London vs. Delhi, 1700 to 2016



Beside the comparison between London and Delhi, Iran has made a different way to control the air pollution. In Iran, the first law on air pollution control was approved by the parliament in 1977 .In 2000, a program called the Comprehensive Program for Combating Air Pollution in Tehran was designed and approved to achieve healthy and breathable quality air in the capital within 10 years. This program includes the following 7 axes: Vehicle standardization, decommissioning of obsolete cars, public transportation promotion, fuel quality improvement, vehicle technical inspection, traffic management, and public education. This program was implemented in cooperation with the Ministry of Industry, Ministry of Petroleum, Environmental Protection Organization, Tehran Municipality and the Traffic Police (Malakooti, 2010).

The amount of pollutants in the air depends on the following factors: previous concentrations of pollutants, chemical processes, transport and diffusion of pollutants, meteorological parameters and vehicle emissions. Meteorological parameters that affect the amount of air pollutants include radiation, wind, temperature, turbulence, rainfall, humidity and stability (Vardoulakis et al., 2003; Malakooti, 2010).

Climatic parameters related to air pollution

In general, in the discussions related to air pollution and determining the potential for the accumulation of pollutants in each region, three main issues are examined:

I) Sources of pollution and their role in the production of pollutants

II) How pollutants are transported and dispersed

III) The amount of pollutants received at certain distances from the source of pollution

In all the above studies, attention to the climate factors has intense importance. Because these factors directly or indirectly affect the production of pollutants, their emission, and distribution, as well as the number of pollutants received in different places. For example, the fuel required to heat a given space depends on the ambient temperature. To control pollution, by changing the type of fuel used in the transportation sector, which is an important part of pollution sources, the amount of pollution can be significantly reduced, or by refining and purifying, the number of pollutants before entering the atmosphere can be reduced. However, in some cases, due to technical, scientific, and economic issues, it is not possible to eliminate or limit the contaminant. In such circumstances, using meteorological information and statistics, suitable places are considered for the establishment of contaminant sources so that to maximize the potential of the atmosphere to dilute pollutants and prevent them from moving towards residential sources (Wang, K, 2019).

In the following steps, more research will be done on the climatic parameters affecting air pollution.

Atmospheric humidity can affect the air quality of an area. Water vapor in the atmosphere has a very important effect on the absorption of solar radiation as well as heat radiation reflected by the earth. In this way, it can overshadow the energy and heat balances of the environment and directly or indirectly alter air quality. In addition, in a contaminated area, when relative humidity rises, particles in the air act as central nuclei, collecting water molecules around them and due to the dissolution of gaseous pollutants in this polluted water, fog is produced. Particles in the air sometimes play the role of catalyst due to their special compounds. For example, iron oxides oxidize sulfur dioxide to sulfur trioxide, which then combines with air humidity to convert it to sulfuric acid. Humidity and humid environments are also required for ion reactions and exchanges. Therefore, with increasing relative humidity, due to chemical reactions on the surface of the particles, new pollutants are produced and enter the air, thus increasing the severity of air pollution (Wang, K, 2019).

In the event of temperature variations in the atmosphere, horizontal and vertical shifts might have a direct influence on the formation of air currents, resulting in pollutant transmission. The amount of solar energy received and the amount of reflection of thermal radiation in different parts of the earth (from the equator to the poles) are not the same even very different. This causes the temperature in the horizontal dimension of space in different parts of the earth is not uniform. So that the highest temperature is in the tropics. As the latitude increases, the temperature also decreases to a minimum at the poles. Thermal differences in different regions along with the Earth's rotation cause global and specific patterns of winds, and as explained earlier, winds play an important role in reducing and dispersing air pollutants and reducing air pollution. In addition, in the vertical profile of the troposphere, the temperature is not the same and with increasing altitude, the temperature decreases. In unstable conditions, when the temperature drops by more than one degree Celsius per 100 meters of altitude, warm air rises above the ground, and the colder air replaces it in the upper part. In fact, vertical mixing is done. Under such instability, contaminants disperse rapidly. Conversely, in stable air conditions, where the rate of change of the thermal profile is low (decrease of less than one degree Celsius per 100 meters increase in altitude), especially in conditions where winds are low, the possibility of accumulation of pollution is high. The ascent height of hot air, which is gradually cooled into the temperature of the surrounding air, is called the mixing depth, which in fact indicates the highest extent of contamination.

In addition to the effects of temperature on the horizontal and vertical flows of air masses, with increasing temperature, the rate of chemical reactions of pollutants with each other or with natural compounds in the atmosphere increases. In this way, temperature can affect the production, distribution and accumulation of pollutants (Wang, K, 2019).

Due to the effect of temperature inversion in winter, this concept is also described below:

As mentioned earlier, under normal tropospheric conditions, the temperature decreases with increasing altitude. The decrease in temperature with altitude is also called the vertical temperature gradient, which is approximately one degree per hundred meters of altitude. In such conditions, and especially when the rate of temperature decrease is more than this amount, the air is unstable and as a result, the transfer and dispersion of pollutants are done well. Because warm and light air rises and is replaced by cold and heavy air, and as a result, the pollutants that are close to the earth's surface also rise and disperse. However, sometimes, for various reasons, such as the movement of a mass of hot air over a layer of cold air or the rapid cooling of air adjacent to the earth's surface relative to the upper layers of air, the opposite happens. That is the temperature increases with increasing altitude. This condition is called temperature inversion with inversion. Temperature inversion can also occur at different altitudes. In the sense that sometimes the temperature inversion starts from the earth's surface and extends upwards, which is called the earth's surface inversion. Nevertheless, sometimes the temperature inversion starts from a height above the ground, in which case it is called the upper surface inversion. Creating and maintaining temperature inversion at any altitude of the atmosphere causes air stability at the same altitude. In the inverted state, cold and heavy air is placed at the bottom, warm, and light air at the top, resulting in extremely stable and calm air. In this case, the contaminants are near the ground, ie upside down, which, like a roof, prevents them from moving in a vertical direction. In most air-pollution-catastrophes, such as the December 1952 accident in London, the phenomenon of inversion has been the main cause of the accumulation of pollutants, resulting in increased mortality and morbidity. When the inversion phenomenon occurs, the amount of oxygen in the air decreases due to gradual consumption and the amount of pollutants increases due to their gradual production. This causes the air adjacent to the earth's surface to be severely polluted (Olympics, 2009).

In addition to these factors, there are other factors such as precipitation (causes acid rain), air pressure (effect of low pressure and high-pressure systems on winds and pollutants), day length, and radiation intensity (photochemical reactions) that in this study Due to the high importance of three factors: wind, humidity, and temperature; Most have been described and used in modeling.

Background of the research

The density of PM10 is determined using an Artificial Neural Network in the form of a 24-hour multilayer, according to Reyes and Perez (2002). Despite the fact that the nonlinear model is more accurate than the linear model, the findings of this study suggest that choosing the right input data for modeling is considerably more important in achieving the intended result.

Kukkonen and et al. (2003) focused on model evaluation and comparison of the correlation between PM10 and NO2 using neural network model, linear statistical model and a definite modeling system in urban areas. The results showed that neural network models could be a proposed tool for assessing PM 10 and NO2 concentrations in urban areas.

In an article, Jiang and et al. (2004) used the ANN artificial neural network to predict the API (Air Pollution Index) in Shanghai using meteorological forecast data as input.

Reyes and Perez (2006) estimated a maximum 24-hour pm concentration using an integrated neural network model. There were three categories or classifications of air quality in this study: good (A), poor (B), and critical (C). The results show that for this pollutant prediction, the artificial neural network outperforms linear regression.

Lu and et al. (2006) stated in an article that the two-stage neural network was first used to determine meteorological regimes and then to predict ozone concentrations in Taiwan. Ozone and meteorological data were extracted over a 5-year period (1998-2002). From the Davis Boldin index, the results of clustering method (two clustering approaches) showed that seven, six, seven and five distinct meteorological regimes are optimal at Chitin, Changmin, Chai and King Jin stations, respectively. Ozone-related concentrations in most meteorological regimes had different concentration characteristics based on Waller Duncan's k - ratio t test. The results showed that the accuracy of ozone concentration prediction improved after meteorological regimes were properly classified, and that the multilayer perceptron method was better than multiple linear regression because there was an association of ozone-independent satellites in nature.

Diaz-Robleo and et al. (2008) looked at linear models and multilinear regression to forecast air quality, but found that their accuracy was limited by their inability to anticipate severe occurrences. Using meteorological and PM10 readings, a combination of ANN and ARIMA was utilized to enhance prediction accuracy for a region with limited air quality and regional meteorological data in this study. In comparison to multilinear regression, experimental findings demonstrate that the hybrid model is an excellent tool for improving PM forecast accuracy. With the capacity to process yearly, the hybrid model is capable of receiving 100% and 80% of warnings before the weather becomes an emergency.

Using the average ideal periods of meteorological elements and the concentration of pollutants, Hurst et al. (2009) developed an artificial neural network to forecast the concentration of air pollution hours. He served as a sort of multilayer neural network in an urban area with low traffic to construct a model for forecasting SO2, NO2, PM 2.5, and PM 10 concentrations. Meteorology was monitored, and pollution concentrations were calculated. When each input variable was utilized on average, a novel technique based on general linear models was proposed for determining the mean interval. As a result, the model's input variables are chosen using an objective technique. The information on the average value of several parameters over the last few hours to estimate pollutant concentrations is the same or higher than the value at the time of prediction. The goal of this model is to utilize a numerical climate forecasting model to anticipate portion of the input data that is still unknown at the time of forecasting. Long-term averages, which are utilized as inputs in the proposed technique, are predicted to result in lower input errors and higher model accuracy.

Kurt and Oktay (2010) mention a three-day-old paper about employing neural networks to anticipate air quality indicators with spatial models. The pollutants SO2, PM2.5, and PM10 are principally responsible for urban air pollution, and they are notoriously difficult to predict. This study used neural networks to build a number of spatial models to anticipate air pollutants. A series of experiments for an Istanbul region were used to assess the accuracy of these models' predictions, and the results were published. The findings demonstrate that spatial parameters in geographical models are better than those in non-geographical models. All other models are outperformed by the 3D model based on distance. Between August 2005 and August

2006, the models were put to the test (approximately 1 year). The most basic proposed geographical model makes use of air quality indicators from a nearby location. Two adjacent regions are utilized instead of one in a second model. The distance between the triangle region and the area where the amount of air pollution is expected is used in the third model. At least two distinct sets of locations have been used to test each model. The results have been quite positive. Geographic models always have less inaccuracy than non-geographic models when close surrounding areas are selected.

Siwek and Osowski (2012) in his research entitled that improving the accuracy of predicting PM 10 pollutant by wavelet and a set of neural predictions, They have predicted the system of PM10 concentration in air. This work is based on the application of wavelet deformation and multiple predictions in the set. The important point of this approach is the analysis of data into wavelet coefficients and the use of individual time series predictions related to wavelets at different levels. The use of this technique breaks down the forecasting problem into several simpler tasks, thus making it possible to increase the accuracy of the final forecast. Another innovation of the proposed approach is two-step prediction using an additional neural network for group integration. It was found that the use of this two-step prediction method improves the accuracy of pollution prediction. An important advantage of the proposed approach is that it covers very accurate information about air pollution, reaction mechanisms, sources of meteorological pollution, as well as nonlinear relationships between predictor variables.

Mihalache et al. (2015) used the ANFIS model to predict the concentration of PM particles for short-term conditions. The ANFIS technique was tested for three datasets including all chapters specific to regions of Romania. According to the type of data set, the production method of fuzzy inference system and the optimization method were better identified. The predicted model is more than standard, and can also be used for PM to warn the population when the information extraction concentration is useful for knowledge-based modeling.

The following study can be used to use the Emotional artificial neural network in engineering sciences. Because, as mentioned before; Emotional artificial neural network has not been used to model air pollution and dissertation innovation is present.

Nourani et al. (2019) investigated the performance of three Markovia artificial and neural models based on artificial neural networks for monthly prediction one and three steps ahead, which is the most significant parameter in any hydrological study; reviewed. The following are the models given in this study: FFNN, as a model based on classic ANN, Wavelet-ANN (Artificial neural network with wavelet), as a hybrid model and Emotional-ANN (Emotional artificial neural network), as a modern generation of models based on artificial neural networks. Rainfall was predicted using these models at seven sites in Northern Cyprus. Each input was tested in two different circumstances. Scenario 1 is used to forecast rainfall at each station using data from prior periods. In Scenario 2, the data from the central station, in addition to the data from each station, has been included into models as exogenous inputs. In comparison to previous FFNN and WANN models, the EANN model performed better, notably in the three-stage prediction. The EANN model outperforms other models because of its capacity to resist multi-step forward error amplification. Furthermore, the findings revealed that Scenario 2 outperforms Scenario 1, with modeling efficiency gains of up to 17 percent and 26 percent in the calibration and verification stages, respectively.

In one of the most recent studies on artificial intelligence and air pollution, Shams et al. (2020) forecasted air carbon monoxide using an artificial neural network vs multiple regression. The purpose of this study was to anticipate carbon monoxide levels in Tehran's air. Daily data from Tehran air quality monitoring stations, climatic variables, temporal characteristics such as one-day delay and traffic parameters, and an air-pollution-prediction model related to urban mobility in Tehran are all included in this study. In multi-criteria decision-making, the importance of assessment indicators is extensively discussed. Gray relationship analysis was used to prioritise the characteristics that influence air pollution. Finally, the results of a linear regression model and an artificial neural network were compared. The correlation coefficient and mean squares error for the neural network model were R= 0.72 and RMSE= 0.69, respectively, whereas the linear regression model had R= 0.10 and RMSE= 11.747. According to the findings of this study, the neural network model has a smaller error than the linear regression model. According to the results of the sensitivity analysis, the factors of hot and cold seasons, one day delay, two day delay, days of the year, and months of the year had the greatest impact on the concentration of monoxide in Tehran.

As can be seen, a few researches have been done on the modeling and prediction of air pollutants in different cities and regions, but none of them have used and compared all models of artificial neural network, adaptive neural-fuzzy inference system and artificial neural network as an emotional non-sensory neural network together. The use of Emotional artificial neural network to model air pollution is also a new step of this research and the data of London city and modeling for air pollution of London city indicate that the subject is new.

CHAPTER 3

Research Methodology and Methods

In the present study, Artificial Neural Network models, Adaptive Neuro Fuzzy Inference System and Emotional Artificial Neural Network based on data from London have been used. In the following, the study area, the data used in the research and the methods used to develop forecasting models are described.

Study area

London is the biggest city and known as the center of United Kingdom. This city is known as the largest administrative, communication, commercial, political, industrial, cultural and military hub of this region. For NO2 and particle matter, London's air quality requirements are greater than those set by the World Health Organization (WHO). These pollutants, for example, aggravated a plethora of health problems in the capital in 2010, resulting in the loss of 140,743 years of life. – Up to 9,400 people might have died because of this– With a cost to the economy of £3.7 billion Poor air quality in London is a serious public health concern: air pollution is the second most important factor in determining one's health, behind smoking. If London is to maintain its status as a worldwide financial center, it must solve the issue of air pollution (Laybourn-Langton, et al, 2016).

Road travel, specifically diesel cars, is the primary source of air pollution in London. Diesel cars account for almost 40% of all NOx emissions in London, and once is addressed, it would be difficult to clean up the city's climate. According to new modeling requested for this study by King's College London, In inner London, measures decreasing the number of diesel cars to 5% of the fleet and increasing cleaner alternatives in other vehicle categories would bring 99.96 percent of the city into compliance with legal NO2 levels. The study's main conclusion is that London must progressively phase out diesel automobiles over the next decade and beyond in order to decrease air pollution levels to legal and, ideally, healthy levels (RCP 2016).

Pollution from both within and outside London has an impact on the quality of the city's air. Particles having a diameter of 0.1 to 1 mm will remain frozen for weeks, allowing them to travel great distances. Around 75% of PM emissions in Greater London are thought to originate beyond the city limits (Howard2015), with transboundary PM2.5 having the biggest influence on mortality (Walton et al 2015). Only 18% of London's atmospheric NO2 comes from outside the city (Howard2015), meaning that the majority of NO2's mortality impact is due to the city's origins (Walton et al 2015). The major focus of this paper is on the steps that can be implemented in London (See Figures 3 and 4). Domestic and non-domestic coal, rail, aviation, and non-road mobile equipment like cranes and generators are among the other outlets. According to Figures 5 and 6, diesel automobiles are not only the most significant single source of NOx emissions in London, but they are also the most significant contributors to road transport air pollution. As a result, the rest of this study, as well as the policy suggestions in chapters 4 and 5, focuses on road transportation, notably diesel automobiles.

Figure 3.

Sources of NOx, 2010, Greater and Central London, Roads (Laybourn-Langton, Quilter-Pinner, & Ho, 2016).

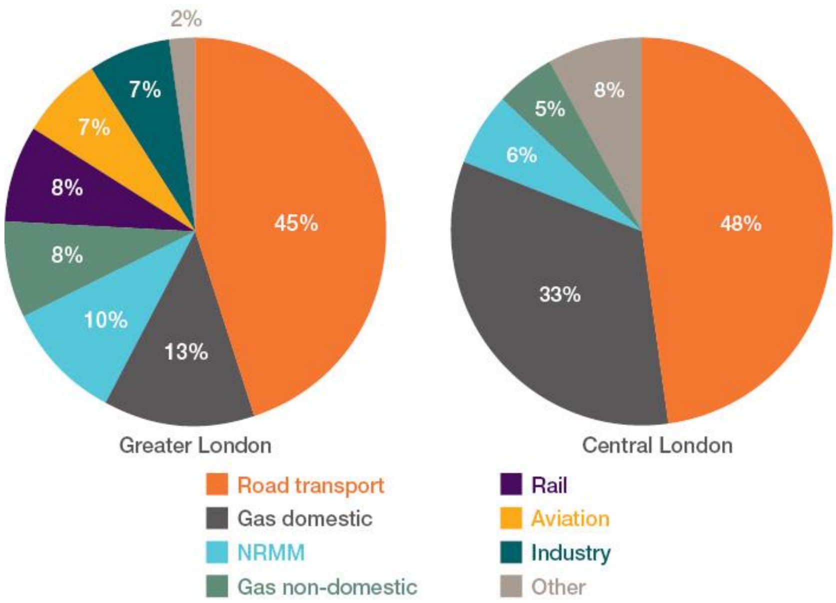


Figure 4.

Sources of PM10, 2010, Greater and Central London, Roads (Laybourn-Langton, Quilter-Pinner, & Ho, 2016).

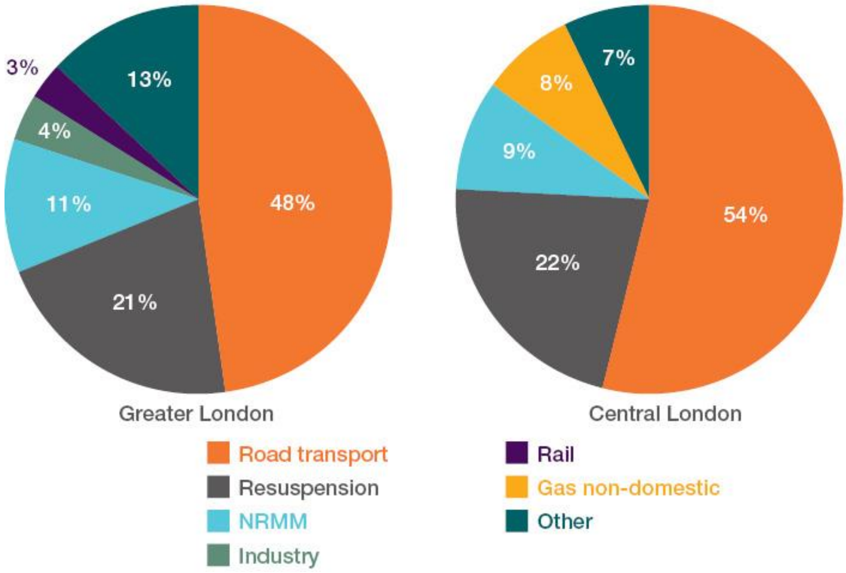


Figure 5.

Sources of NOx, 2010, Greater and Central London, Cars (Laybourn-Langton, Quilter-Pinner, & Ho, 2016).

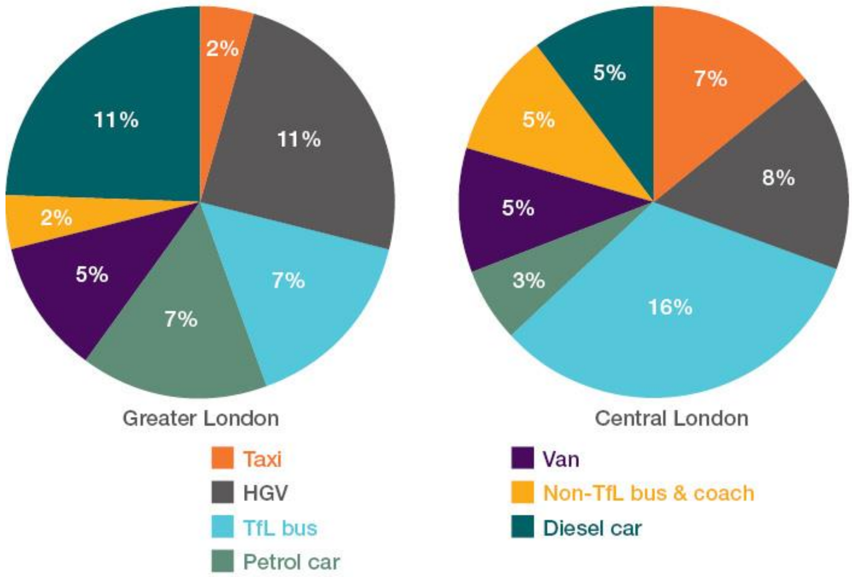


Figure 6.

Sources of PM10, 2010, Greater and Central London, Cars (Laybourn-Langton, Quilter-Pinner, & Ho, 2016).

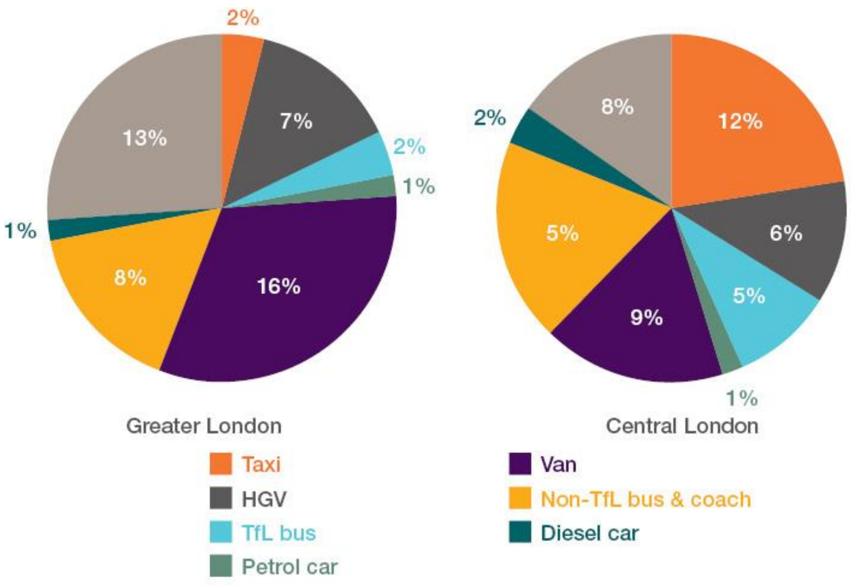
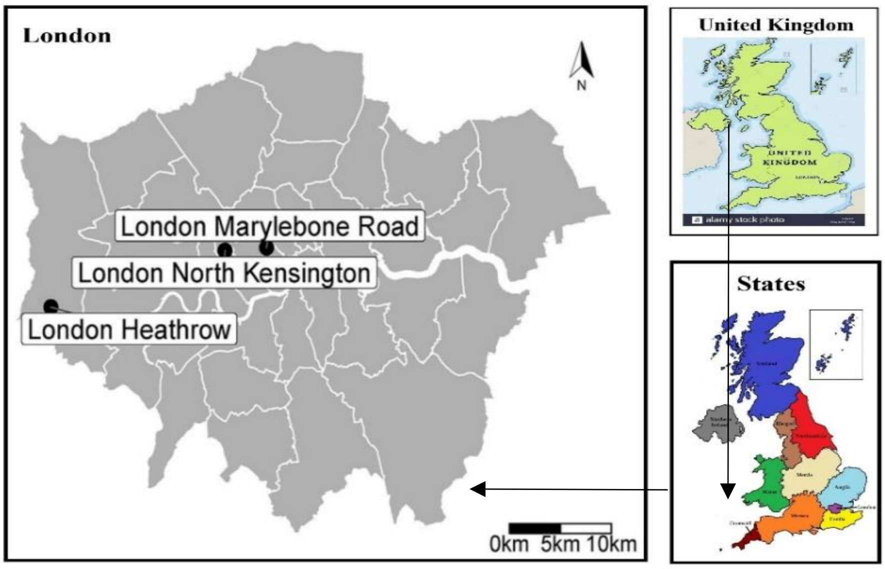


Figure 7 shows the map of the United Kingdom, then the map of the city of London from the United Kingdom, and finally the map of the air-quality-control stations of the city of London.

Figure 7.

Air Quality and Meteorological Monitoring Sites in London



The Meteorological and Air quality monitoring sites which is used for this study are: London Marylebone Road, London North Kensington, and London Heathrow. The mentioned stations provided the required data for our study.

Used Data

Based on a review of the technical literature, it was concluded that for modeling air pollutants, two categories of data are often used, which are: a) air quality data (including the pollutant itself in the past), b) meteorological data (including temperature and humidity) (Daly and Zannetti, 2007). The description of data uses can refer to the kind of data, utilized for designing a plan for predicting pollutants. Four type of impressive pollutants such Nitrogen dioxide, Sulfur dioxide, Particulate matter 10 and Particulate matter 2.5 are used. Measured in Micrograms per Cubic Meter of Air (ug/m3) and the data has used, measured by the time of day per month between 2010 and 2019. In this study, time series of temperature, humidity, and pollutant data source was used as input. Meteorological information including temperature and humidity was received from the reputable site of (rp5.ru). In addition, Air Quality data has been utilized from the London Data Store, which is received from the mayor of London (data.london.gov.uk). In the present study, some preventive actions need to implement in order to not be complicated and acquire an approximately proportional, so attempt to enter hour and day to the mentioned problem has got lots of benefits. In which, itself determines the more polluted hours and the more polluted days of the week. For this purpose, four hours 13, 16, 19 and 22 were presented to the model. In addition, days from 1 to 7 were included in the model to determine the days of the week as a coefficient and to create strength in the obtained results.

The description of data uses can refer to the kind of data, utilized for designing a plan for predicting pollutants. Four type of impressive pollutants such Nitrogen dioxide, Sulfur dioxide; Particulate matter 10 and Particulate matter 2.5 are used. Measured in Micrograms per Cubic Meter of Air (ug/m3) and the the data has used, measured by time of day per month between 2010 and 2019.

Each day, four data points are evaluated, which are connected to the hours of 13, 16, 19, and 22 local time, i.e. England, which were chosen as the hours when pollution levels fluctuate significantly. Data was collected for roughly ten years, beginning on January 1, 2010, and ending in June 2019. Each day, four data points are evaluated, which are connected to the hours of 13, 16, 19, and 22 local time, i.e. England, which were chosen as the hours when pollution levels fluctuate significantly. Data was collected for roughly ten years, beginning on January 1, 2010, and ending in June 2019.

Table 2 shows the list of variables utilized as input to the models, as well as their relevant information.

Table 2.

List of Variables Used as Input to Models

Variable Input	Symbol	Unit	Range	Average	Standard deviation
Temperature	T	℃	-27.4 up to 34.3	8.7	11.16
Humidity	H	%	10.0 up to 99.0	74.8	16.44
NO2	-	µg / m3	21.0 up to 95.6	55.2	13.57
PM 10	-	µg / m3	11.8 up to 52.1	25.0	6.11
PM 2.5	-	µg / m3	5.9 up to 36.5	15.6	5.20
SO2	-	µg / m3	-2.4 up to 14.0	3.4	1.95
Time of day per month Index	DHI	-	-	-	-

The time series related to the data including Temperature, Humidity, NO2, PM10, PM2.5 and SO2 pollutants data are shown in Figures between 8 and 12, respectively.

Figure 8.

Temperature Time Series for 10 Years

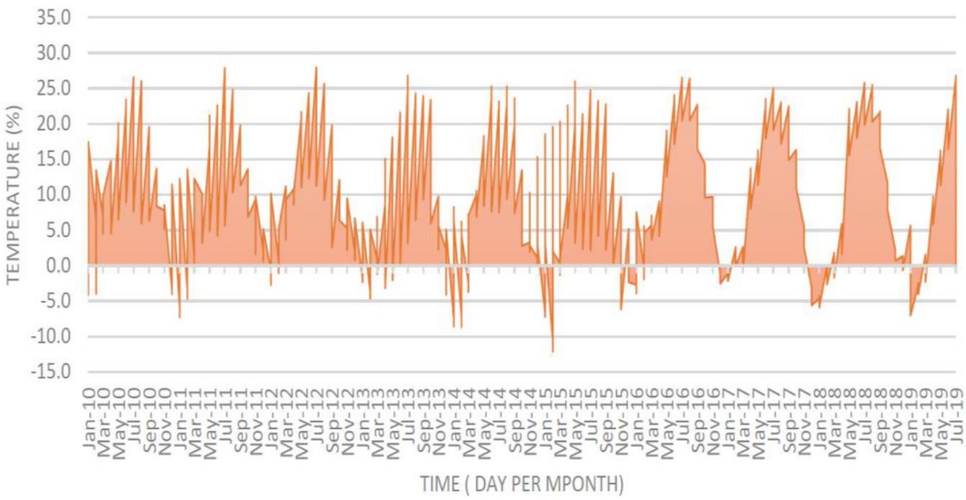


Figure 9.

Humidity Time Series for 10 Years

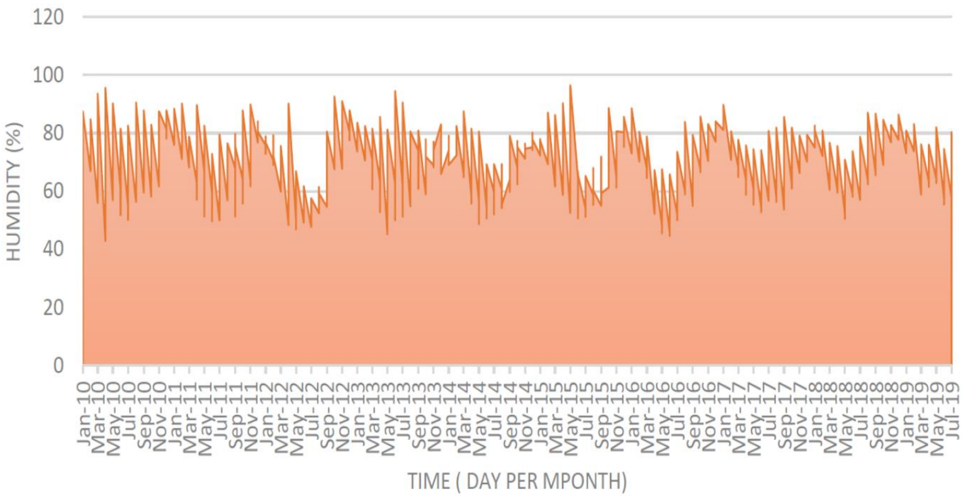


Figure 10.

NO2 Time Series for 10 Years

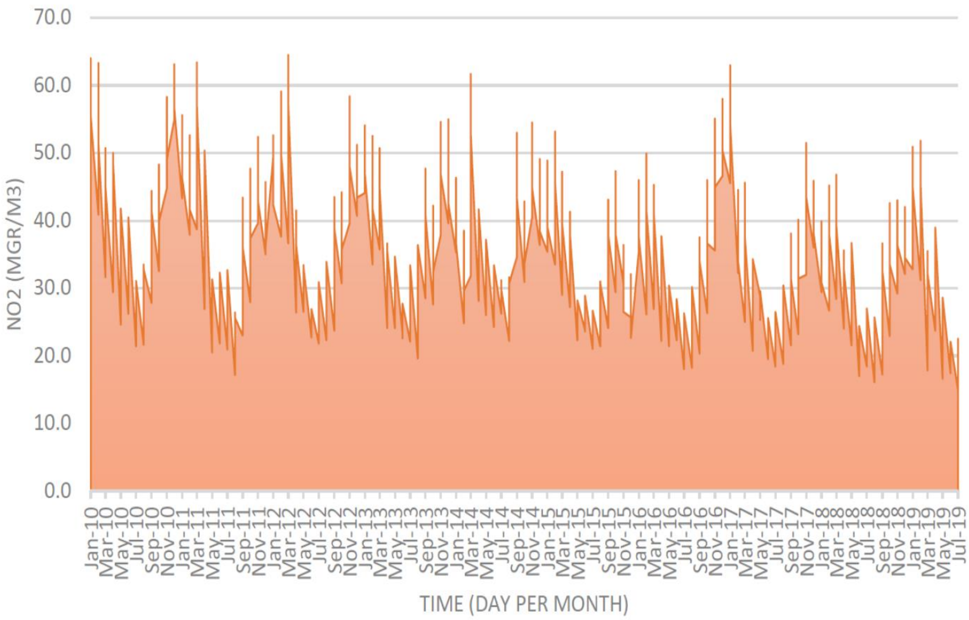


Figure 11.

PM10 Time Series for 10 Years

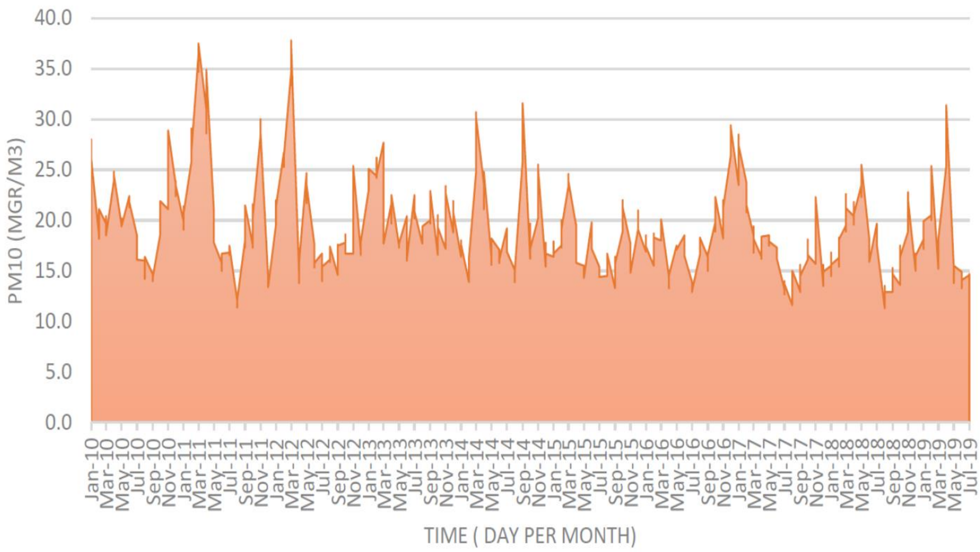


Figure 12.

PM2.5 Time Series for 10 Years

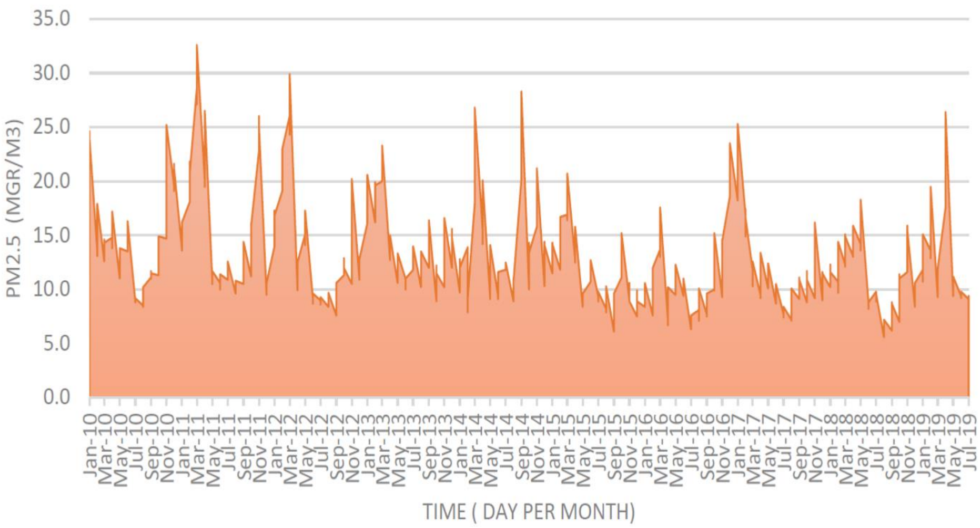
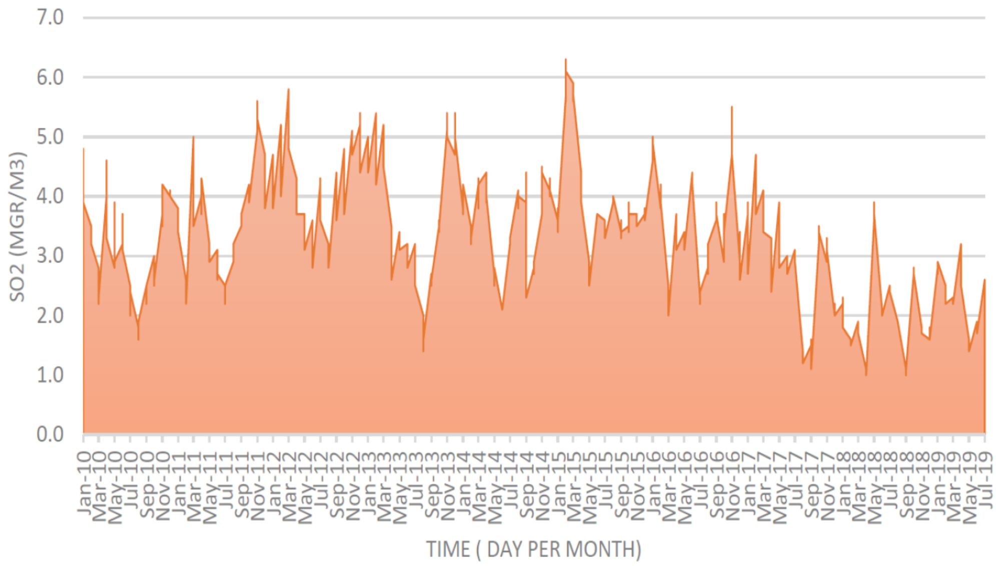


Figure 13.

SO2 Time Series for 10 Years



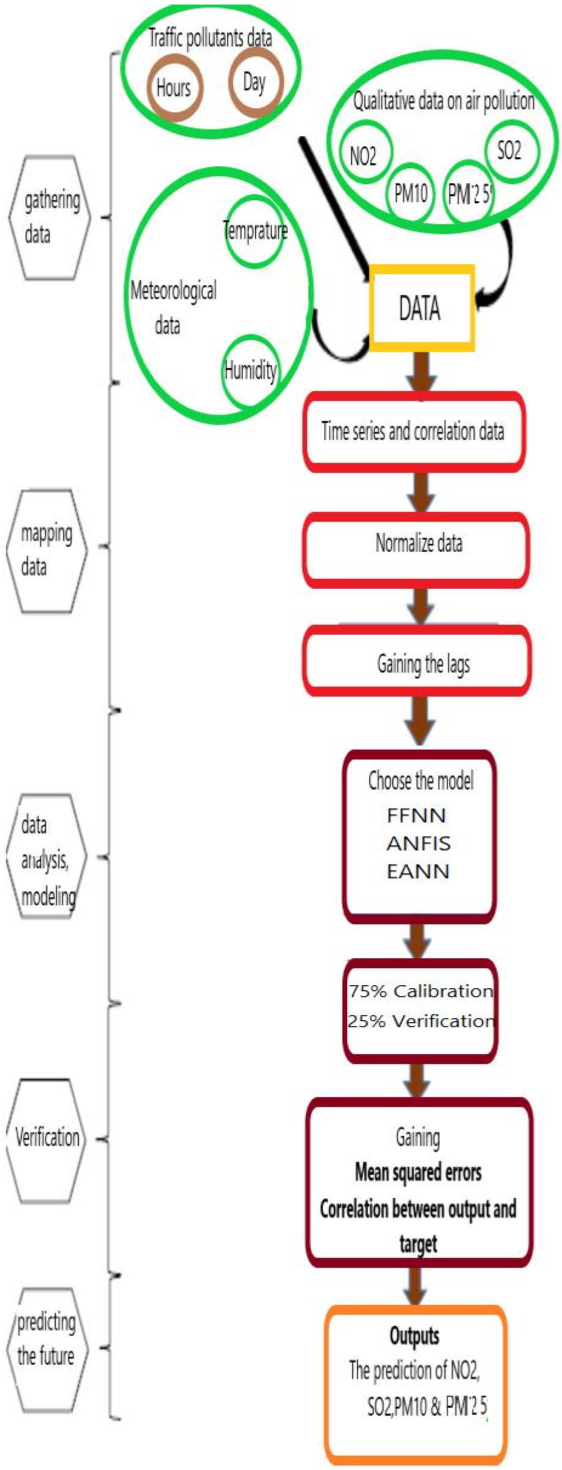
Regarding pollutants, it should be noted that according to the Environmental Protection Agency (EPA), the American standard, which values the air quality index (AQI) above the range of 150, is considered unhealthy for all groups in society. Considering the AQI standard, the figures indicated that all the four types of Pollutants, NO2, PM10, PM2.5, and SO2 place above the line of unhealthy rate, so it doesn't mean London has healthy weather. Nevertheless, all four types of pollutants have been considered and modeled in this study.

Research method

In this research, Artificial Neural Network, Adaptive Neuro Fuzzy Inference System, and Emotional Artificial Neural Network methods have been used to predict pollutants for the air of London. In the following, each of the above methods will be briefly explained. Figure 14 shows the research method schematically.

Figure 14.

Research Methods and Steps in General and Schematic



Feedforward Neural Network (FFNN)

In recent years, It has witnessed a steady shift away from purely theoretical research and toward practical research, particularly in the field of information processing, for issues that have no solution or are difficult to address. With this in mind, theoretical research of free-model intelligent dynamic systems based on this category of "Artificial Neural Network" systems is gaining popularity. They are based on real-world facts. Intelligent systems are developed by creating dynamics that, by analyzing experimental data, convey the knowledge or law behind the data to the network structure.

Implementing the amazing features of the brain in an artificial system (a man-made dynamic system) has always been tempting and desirable. There are many researchers which have worked in this field over the years. However, the result of these efforts, regardless of the valuable findings, has been the growing belief in the principle that (the human's brain is unattainable). Emphasizing that, apart from metaphysics, the far-reaching reach of the ideal (natural intelligence) can be accepted by the inadequacy of existing human knowledge of neural physiology. It should be acknowledged that the excellence of the goal and the insufficiency of existing knowledge have motivated more and more research in this field. As we have seen today, such activities occur in the form of artificial neural networks. Most people, who are familiar with such systems, admit that their names are exaggerated, although this exaggeration indicates the desirability as well as some similarities between such systems and natural systems, but it can, to some extent, create a contradiction between what artificial neural network provides and what their name implies. Therefore, when talking about neural networks, one should specify the limits of expectations, perceptions, possibilities, and similarities. Before defining these boundaries, let us first look at what neural networks mean (Grossi et al, 2007).

Layers and weights are the components of a neural network. Communication between members is also important for network activity. In general, neural networks have three types of neural layers:

I) Input layer: Raw data from the network is received.

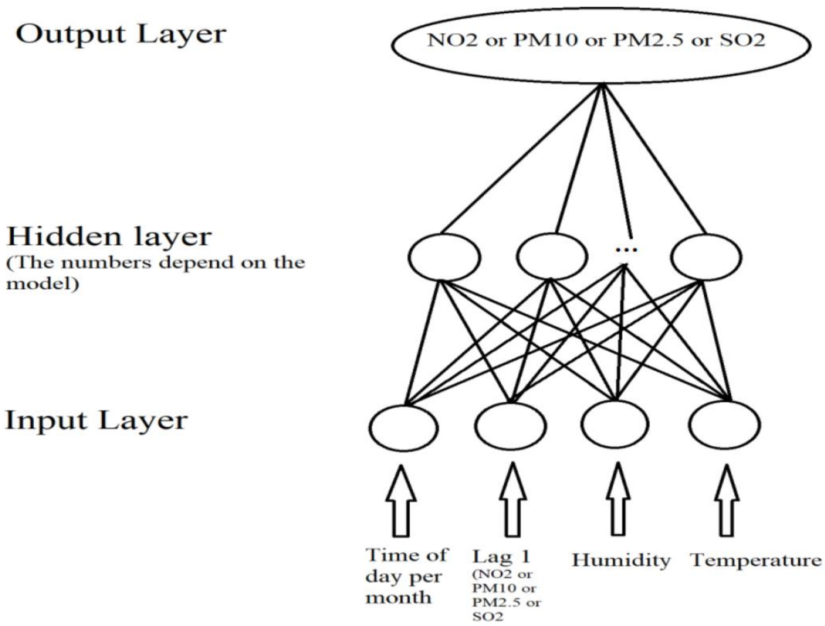
II) Hidden layers: The inputs and the weight of the link between them and the hidden layers influence the performance of hidden layers. When a hidden unit should be triggered, the weights between the input and hidden units decide when it should be activated.

III) Output layer: The activity of the hidden layers and the weight of the relationship between the hidden layers and the output determine the output unit's performance.

Figure 15 provides an overview of the artificial neural network in this study.

Figure 15.

Input, Hidden Layer, Output of Feedforward Neural Network



There are single-layer and multi-layer networks, with single-layer organizations being the more common and having higher computational potential than multi-layer organizations. Layers, rather than following global numbering, number units in multilayer networks.

Both layers of a network are connected by weights, and in fact connections. There are several types of weight connections in neural networks:

The majority of connections are of this sort, in which the signals only travel in one way. From input to output, there is no feedback (loop). Each layer's output has no impact on the same layer, which is referred to as Lead.

The data has fed from the top layer nodes to the bottom layer nodes, is Feedback layer.

The output of each layer's nodes, known as Lateral, is utilized as the input of nodes in the same layer.

Perceptron is a sort of neural network that may be divided into Single-Layer Perceptron (SLPs) and Multi-Layer Perceptron (MLPs). Precursor neural networks include perceptron neural networks. A single-layer perceptron can only categorize discrete linear issues; for more complicated problems, additional layers are required. One or more intermediate levels make up multi-layer feeder networks. Because each neuron in one layer is linked to all the neurons in the next layer, the multilayer perceptron of a network is totally interconnected. If some of these links are missing, the network will be incomplete. When the network is said to consist of n layers, only the middle and outer layers are counted and the input layer is not counted because these neurons do not math. Therefore, a single-layer network is a network with only one outer layer.

The transfer function is a linear or nonlinear function. The transfer function is used to adjust the properties of neurons to solve a problem.

I) Step or threshold transfer function: This transfer function, if "n" is less than zero, gives zero output and if "n" is more than zero or equal zero, output is one. This transfer function is used to classify inputs into two classes. This function is used mostly in neurons that make perceptron networks.

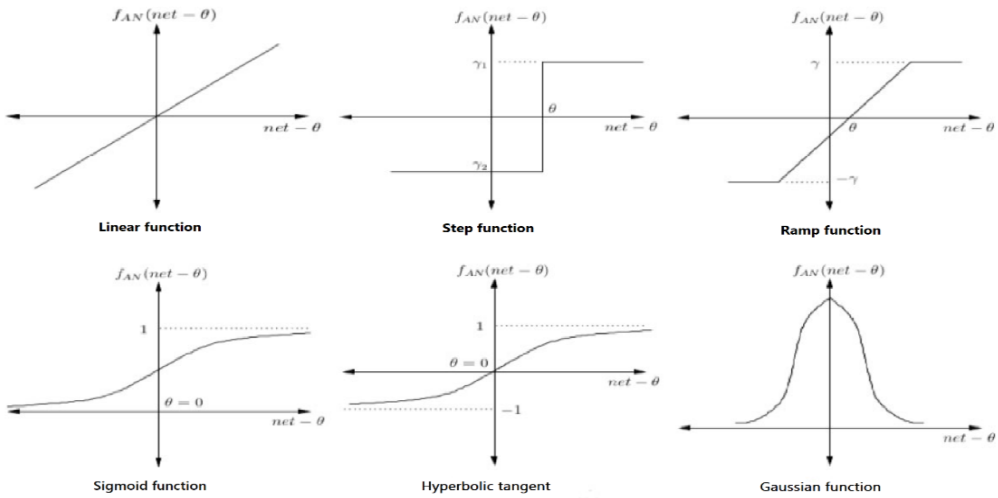
II) Linear Transfer Function: Neurons that use this transfer function are used for linear approximation in linear filters. This input function with the linear sum of the inputs as output.

III) Sigmoid transfer function: The related transfer function, acquire the amounts of input in the range of -∞ until +∞ and produces the output between 0 and -1. By changing the slope of the function, its linear operating range can be changed.

IV) Hyperbolic tangent transfer function: Acquiring the amounts of input in the range of -∞ until +∞ and produces the output between -1 and +1 (Zare Abyaneh et al, 2016). Figure 16 shows some examples of transfer functions.

Figure 16.

A Few Examples of Transfer Functions (Zare Abyaneh et al. 2016)



In general, artificial neural network learning algorithms are expressed. In presenting the differential equation, it is assumed that the processes are continuous. If ones wants to simulate artificial neural networks on a computer, it is desirable to provide differential equations of perfection. However, most of today's work is done on digital computers. Therefore, providing differential equations is the most appropriate solution because these equations can be easily returned to computer programs. For this reason, it is better to use differential equations (Wasserman, 1989).

The purpose of training a network is to adjust its weights so that output can be generated using a set of inputs. For the sake of brevity and simplicity, these output input-output categories can be considered as a vector. In training, it is assumed that each input vector forms a pair with a target vector that expresses the desired output. This pair is called a sequential or educational pair. A number of educational couples usually develops a network. Before starting the network training process, all weights should start with small random values. This ensures that the network will not be saturated with large amounts of weights and some training damage will be prevented.

There are two types of training algorithms: supervised and unsupervised. Supervised training necessitates the use of input and target vector pairs (desired output). An educational pair is a collection of arbitrary input and output vectors connected with it. Typically, a network is built using a number of such training pairings.

The network output is computed and compared to its corresponding target vector using an input vector, and the difference between the calculated and intended outputs, known as the error, is transmitted backwards across the network, followed by the weights. They're tweaked and altered using an algorithm that aims to reduce inaccuracy. Consecutive training vectors are utilized, errors are calculated, and weights for each vector are changed until the error for the total training unit achieves a small acceptable value. Of course, there are methods in which, first, all the vectors in the training category are presented to the network and errors and weight changes are calculated for each vector, and then the sum of the weight changes is applied to the weights together.

It is difficult to imagine such an educational mechanism in biological systems. For this reason, although this method has been very successful in terms of application, those who believe that artificial neural networks must constantly use the same mechanism similar to the human brain have disliked it.

Supervised education has also been criticized for its many practical successes, as it is biologically unlikely and unreasonable. It is hard to envision a brain-based training system that analyzes actual and intended outputs and propagates prior adjustments backwards through the network. If such a mechanism exists in the brain, the questions arise: where do the desired output patterns come from? How can a child's brain run a self-organizing algorithm that is present even in the early stages of brain development? Unsupervised education is a more probable and sensible model of learning in the biological system.

The algorithm developed by Kohunen in 1984 and a number of other researchers does not require a target vector for the output, so no comparison is made between the actual outputs and the predetermined ideal solutions. The training category in this case only consists of input vectors and modulates the network weights training algorithm to produce coordinated output vectors. This means that by using one of the vectors in the training category or a vector that is sufficiently similar to the vector in the training category, the same output pattern is generated. For example, in such a method, input patterns can be categorized according to their degree of similarity. In this method, by presenting the same input patterns, the same nerve cell is stimulated. As a result, the educational process extracts the educational category's statistical features and groups comparable vectors. A certain output vector will be generated if a vector of a specific class is used as input to the network, but there is no way to predict which output will be produced for a given class of vectors. As a result, after the training process, the outputs of such networks must generally be transformed into an understandable form. This is not a big problem, because the network's connections between input and output are typically obvious to spot.

The other component is reverse error propagation algorithm training. There was no theoretically ideal algorithm for teaching multilayer artificial neural networks for many years. When single-layer networks were discovered to be far more limited in what they could give and learn, the entire field of research began to collapse. The reverse diffusion method contributed significantly to the revival of interest in artificial neural networks. Reversal propagation is a method for training multilayer artificial neural networks that uses a methodical approach.

The law of error propagation has two major pathways. The first is termed the road of departure, and it involves applying the input vector of a multilayer network of perceptrons and propagating its effects via the middle layer to the output layers. The output vector formed in the output layer produces the real response of the perceptron multilayer network. The network parameters are assumed to be constant and unaltered throughout this journey. The return path is the second option. Unlike the first path, the parameters of the second path are modified and adjusted in accordance with the error correction legislation in this path. After computing the error value, it is spread throughout the network in the return path from the output layer and through the network layers. Because this recent distribution contradicts the synapses' weight communication channel, the term is chosen after the mistake to describe network behavior rectification. The network parameters are changed in each iteration such that the actual network response is as near to the planned response as feasible.

This algorithm is the most important and most practical algorithm in engineering works. This algorithm is used only for supervised training and the network weights are adjusted by backward speech propagation. The calculated error in this algorithm is the difference between the computational and observational results. The purpose of this algorithm is to reduce the error to complete the training phase. The activation function in the neurons of artificial neural networks in this algorithm is responsible for collecting the multiplied inputs to the desired communication weight.

Training with Lunberg-Marquardt algorithm is expressed in following that This method is a modified version of Newton's classical algorithm that is used to find a suitable solution to problems that need to be minimized. This method considers an approximation for the Haysen matrix in weight change like Newton's method (Haykin, 1994).

$$x_{k+1} = x_k - \left[J^T J + \mu I \right]^{-1} J^T + e \tag{1}$$

In the above relation, “x” neural network weights, “J” Jacobin matrix of network performance criteria that should be minimized, “μ” is a number that controls the training process and “e” is the residual error vector. When “μ” is zero, the above equation is the same Newtonian method that uses the Haysen method, but when “μ” is a large value, the equation becomes a gradient reduction relation with a small time interval. Newton's method has a high speed and the results will be very close to the minimum error. This algorithm has been used in many studies due to the above characteristics. This algorithm has high efficiency and is very stable.

Adaptive Neuro Fuzzy Inference System (ANFIS)

Fuzzy inference systems are a prominent computing paradigm that uses fuzzy sets, IF-THEN rules, and fuzzy reasoning to solve problems. Three conceptual pieces make up the core framework of fuzzy inference systems. The rules are the first section, which includes a number of fuzzy rules. The database, which contains the membership functions utilized in fuzzy rules, is the second portion. Finally, the third portion is the inference mechanism, which performs the inference method using existing rules and evidence to arrive at a plausible result. Mamdani fuzzy models, Sugeno fuzzy models, and Tsukamoto fuzzy models are three forms of fuzzy inference systems that have a wide range of applications.

The difference between these systems is as a result of fuzzy rules and as a result of the procedure for calculating sum and non-fuzzy in them. In this research, Sugeno model will be used, which is explained below.

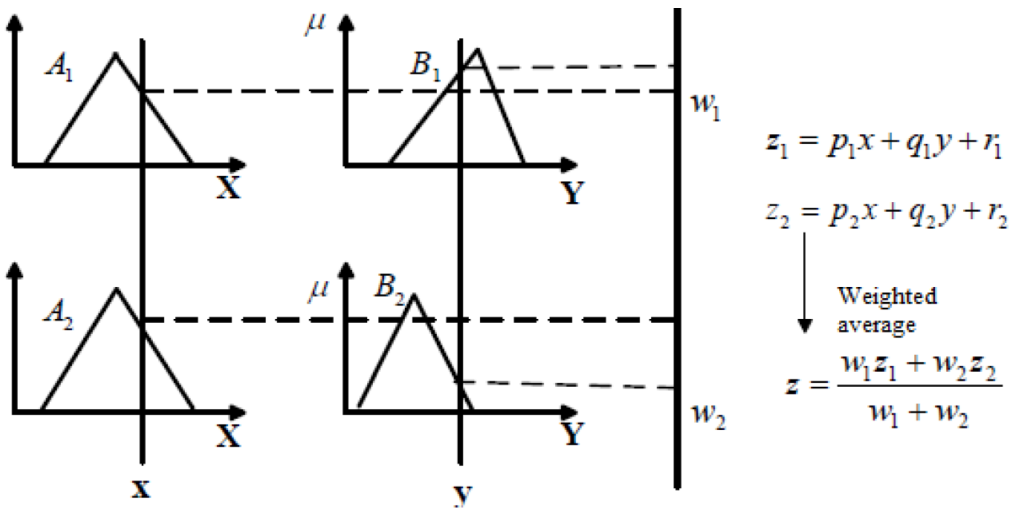
The TSK fuzzy model (introduced by Takagi, Sugeno, and Kang), often known as the Sugeno fuzzy model, is an effort to construct an intelligent system for developing fuzzy rules based on the formiula 2 data set:

If x is A and y is B then z = f(x,y) (2)

The fuzzy sets and z = f (x, y) are a function in the rule's outcome in connection A and B. f (x, y) is usually a polynomial with the variables x and y. If f (x, y) is a first-order polynomial, the fuzzy inference system is known as the first-degree fuzzy model, and if f (x, y) is constant, the fuzzy inference system is known as the zero-degree fuzzy fuzzy model. The fuzzy reasoning technique in the first-order Suguni model is shown in Figure 17. (Gupta et al. 2020).

Figure 17.

Fuzzy Reasoning Procedure in the First Degree Sugeno Model (Jang, 1993)



Because each rule provides a numerical output, the weighted average is used to determine the final result. The weighted average operator is occasionally substituted with the weighted sum operator (w1z 1 +w 2z 2 =z) in practice. As a result, the volume of calculations is lowered once again, particularly during the fuzzy inference system's training phase (Gupta et al, 2020). Fuzzy modeling is divided into two stages that are interconnected conceptually. The first stage is to determine the surface structure, which entails the processes below:

I) Identify the input and output variables that are connected.

II) Decide on the sort of fuzzy inference system to use

III) Determine the order of the result part's equations

IV) Create a set of fuzzy if/then rules

We shall rely only on our understanding of the target system to complete these stages. Receiving information from specialists and others who are familiar with the target system, as well as trial-and-error, are used to supplement this knowledge. The rules characterising the behaviour of the target system in language terms are more or less supplied after the first step of fuzzy modelling. In the second stage, the meaning of these linguistic concepts is determined. The membership functions of each linguistic word and the output polynomial coefficients in the Sugeno model are determined during this stage, which is referred to as deep structure identification. The following steps are included in this step:

I) Selecting an appropriate family of parametric membership functions

II) Use the expertise of experts in relation to the target system to determine the parameters of membership functions

III) Adjusting membership function parameters using optimization and regression techniques (Gupta et al. 2020).

There are two teachable datasets in the ANFIS framework. Polynomial parameters and main membership function parameters (introduction) (follow-up with result). The starting parameters of the ANFIS structure are optimised using a descending gradient technique, and the outcome parameters are solved using a least squares approach. Equation 3.3 is used to represent each rule in the ANFIS structure.

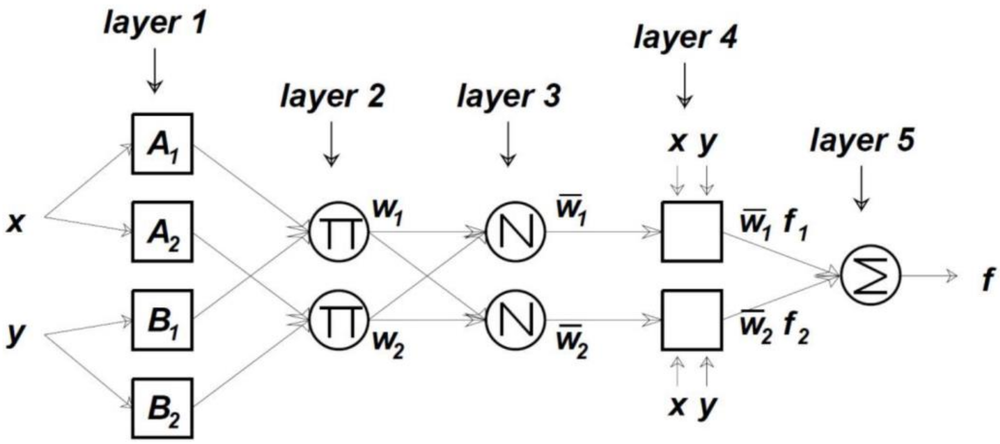
$$\text{IF } x_1 \text{ is } A_{1,j} \text{ AND } x_2 \text{ is } A_{2,j} \text{ AND } \ldots \text{ AND } x_n \text{ is } A_{1,j} \qquad (3)$$

$$\text{THEN } y = c_0 + c_1x_1 + c_2x_2 + \ldots + c_nx_n$$

In regard to 3, "n" stands for the number of inputs, "y" stands for the model's outputs, and "ci" stands for the outcome parameters, which are established during the training phase. The overall output is calculated using the weighted average since each rule has a defined outcome (as opposed to a fuzzy output). Various duties are allocated to successive levels in the Sugno-type ANFIS structure, such as generating a stepwise purification procedure for the model. There are two stages to the learning process: forward and backward. The starting parameters are fixed throughout the forwarding process, and the output parameters are optimised using the least squares technique. The initial parameters of the membership functions for the input variables are modified using a descending gradient technique in the regression process. The weighted average of the output parameters is used to determine the output. The post-diffusion method is used to change the preceding settings for each output mistake (Gaung et al, 2008). The construction of an adaptive fuzzy neural inference system is shown in Figure 18. Circular nodes indicate fixed nodes, whereas square nodes represent nodes with learning power parameters in this system. (Pollen that adapts to the environment.) The ANFIS system includes five levels, as depicted in Figure 18.

Figure 18.

Adaptive Fuzzy Neural Inference System Structure (ANFIS) (Jang, 1993)



The first layer (input and output layer of the membership function): In this output layer, each node is:

$$O_{1,i}=\mu_{B_{i-2}}(y) \quad \text{for } i=3,4 \qquad O_{1,i}=\mu_{A_i}(x) \quad \text{for } i=1,2 \tag{4}$$

All nodes are fixed in the second layer (rules layer). This layer multiplies the second layer (the rules layer) to power each rule: all nodes are fixed in this layer. This layer uses multiplication algebra to indicate the power of each rule, as seen in Equation 5:

$$w_i=\Pi\mu_{A_i}(x_j), i=1,2 \quad j=1,\ldots,n \tag{5}$$

Each node in this layer is created by multiplying the input values from the previous layer. The result indicates rule i's executive authority, with the variable xj having linguistic value for Ai. Normalization layer (third layer): The power of the rule (law) is normalised in this layer, as seen in the following relationship:

$$\overline{w} = \frac{w_i}{\sum w_i} \tag{6}$$

The ith rule in equation 6 is wi executive authority. This layer has the same number of nodes as the preceding layer. The rule for the collection of executive power rules is calculated by this layer of executive authority.

The fourth (adaptive) layer is as follows: Each node in this layer is a linear function, with its coefficients modified using a mix of least squares approximation and propagation.

$$\overline{w}_i f_i = \overline{w}_i (c_0 + c_1 x_1 + c_2 x_2 + \ldots + c_n x_n) \tag{7}$$

The results of the fifth layer (output layer) are acquired as a collection of output nodes from the preceding layer.

$$\sum_i \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{8}$$

The output of the ith node in the preceding layer is w I f I in equation 8 The final result is linear. However, the parameters are logically nonlinear (Gaung et al, 2008).

Emotional Artificial Neural Network

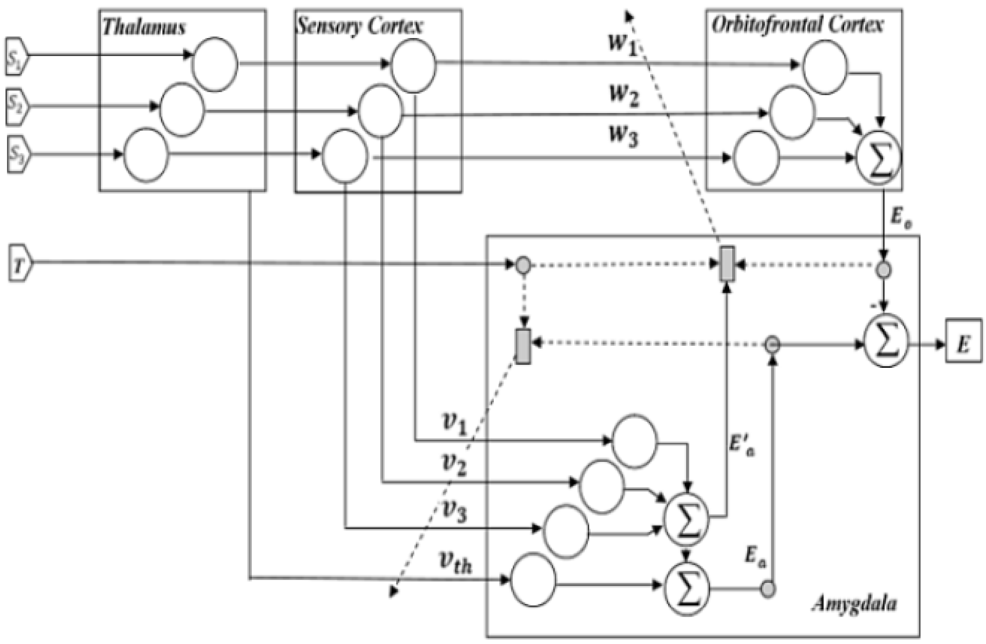
In this part, we will look at how the Emotional artificial neural network came to be and how it works. Following the failure of the artificial neural network and the adaptive fuzzy neural inference system in recent years, researchers have turned to the Emotional artificial neural network. The construction of the Emotional artificial neural network and how to use it in the current investigation are given in the following sections.

The limbic system of the brain influenced the model structure of the Emotional artificial neural network (Lotfi and Akbarzadeh, 2013). This device is the cause of human emotional life. The use of the Emotional neural network in various applications is due to the unique properties of this part of the brain (Rahman et., 2008) ; (Laus et al., 2004). Rapid response to stimuli due to the existence of short paths and the existence of a part as a modifier of responses and inappropriate reactions are among these features (Abdi et al.,2012).

The Emotional neural network includes the amygdala, orbito frontal, thalamus, and emotional cortex (Moren and Balkenius, 2000). As shown in Figure 19, there is a path to respond to stimuli or inputs. The direct path is fast with limited information load and the indirect path has a slow response with a richer information load (Phelps and Ledoux, 2005).

Figure 19.

The Structure of The Emotional Artificial Neural Network (Lotfi and Akbarzadeh, 2013)



The artificial neural network based on emotional learning of the brain “Brain Emotional Learning (BEL)” was first proposed in 2014 in a study entitled "Monitoring Emotional Learning of the Brain"(Lotfi and Akbarzadeh, 2013). For example, a model with three inputs and one output with fixed lines, data flow, and training lines is assumed. In each section, the number of nodes is equal to the number of inputs except in the amygdala, which has an additional node. In addition, the final output of the network is calculated as follows:

$$E = E_a - E_0 \tag{9}$$

Where Ea and E0 are the outlets of the amygdala and the orbitofrontal, which are defined as follows:

$$E_a = \sum_{j=1}^{n+1} (v_j \times s_j) \tag{10}$$

$$E_a = \sum_{j=1}^{n} (w_j \times s_j) + b \tag{11}$$

The appropriate weights are V and W, the bias is b, and the input vector is P. (Lotfi and Akbarzadeh, 2013). Additionally, the following formula is computed, which is the expansion connection between the thalamus and the amygdala:

$$S_{n+1} = \max_{j=1\ldots n} (s_j) \tag{12}$$

The existence of the Max operator is insufficient for system identification. This is due to the model's non-derivative nature, which means it can't be used for system identification applications like model-based control techniques. This network may be used to identify systems by changing this section. The following is the proposed technique for changing the extension link:

$$S_{n+1} = \sin[\pi \sum_{j=1}^{n} s_j].\cos[\pi \sum_{j=1}^{n} s_j] \tag{13}$$

Therefore, the network output changes as follows:

$$E_a = \sum_{j=1}^{n} (v_j \times s_j) + v_{th} \times \sin[\pi \sum_{j=1}^{n} s_j].\cos[\pi \sum_{j=1}^{n} s_j] \tag{14}$$

$$E = \sum_{j=1}^{n} (v_j \times s_j) + v_{th} \times \sin[\pi \sum_{j=1}^{n} s_j].\cos[\pi \sum_{j=1}^{n} s_j] - E_0 \tag{15}$$

Where Vth is the weight of the n+1 amygdala expansion link, calculated from Equation15. Thus, the network is prepared for modeling complex nonlinear systems. In fact, by finding the appropriate weights, the network will be able to identify the nonlinear behavior of systems and processes. Thus, in the training phase, we seek to find the optimal weights. If the genetic algorithm does network training proposed by Lotfi et al., 2014 that eliminates the need for us to adjust learning parameters (Lotfi et al., 2014).

In genetic algorithms, we need a number of chromosomes that contain network weights and are defined as follows:

$$Chorom_i = [v_1 v_2, \dots, v_n v_{th}, w_1 w_2, \dots, w_n, b] \tag{16}$$

As illustrated, each chromosome has 2n+n genes, with n being the number of network inputs.

The purpose of this optimization is to minimize the objective function to achieve the ideal network weights. In addition, the objective function is defined as follows, where T_k, S_k and Y_k are the model outputs, the model inputs, and the model objective for the K model, respectively. M is the number of target patterns (Lotfi et al., 2014).

$$fitness_{train}(Chorom) = \frac{1}{m} \left(\sum_{k=1}^{m} \left(Y^k - T^k \right)^2 \right)^{0.5} \tag{17}$$

$$Y^k = E\left(P^k ; Chorom_i \right) \tag{18}$$

The purpose of the proposed Emotional Artificial Neural Network is to achieve an optimal neural network with low computational complexity for the identification of complex and non-linear systems.

Many existing systems are in fact complex and nonlinear, and it is difficult to arrive at a good mathematical model of them (Ugalde rt al., 2015). In addition, a suitable model of the system is required for the design of the controller. Especially for model-based controllers such as MPC-based predictive control, which requires an accurate model of the system (Kittisupakorn et al., 2009). In fact, the accuracy of this model is effective in better system performance. However, also the amount of computational load should be monitored because achieving high accuracy requires more computational load and more complexity (Prakash J. and Srinivasan, 2009). Therefore, finding the optimal materials between the accuracy and speed of the controller is very important. As a result, linear models are used to achieve the same simplicity typically and reduce computational complexity, while real systems behave completely nonlinearly.

In fact, existing plants whose equations are not accessible can be examined from input and output data without sufficient information about the internal structure of the plant itself. The most famous of these methods are artificial neural networks; Because they can identify a system whose only inputs and outputs can be measured and provide a model for it (Chen and Billings, 1992). The multilayer perceptron neural network is one of the most widely used. The structure of the neural network model for each output is as follows.

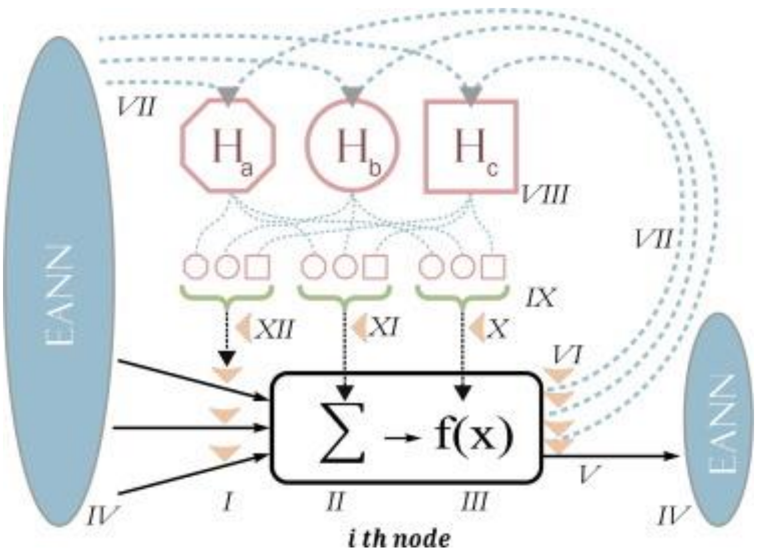
$$y_i = \sum_{j=1}^{N_1} f\left(w_{ij}\left[\sum_{k=1}^{n} f\left(w_{jk}x_k + b_1\right)\right] + b_2\right) \qquad i = 1,\ldots,N_2 \tag{19}$$

Now, if we want to examine Equation 12 in terms of complexity, due to the existence of the hidden layer, its computational complexity is O (n * m). “n” is the number of inputs and “m” is the number of hidden layer neurons. Neural network inputs can include current and past inputs as well as past outputs.

Emotional Artificial Neural Network is the new version of classic networks that contains artificial emotion units, which can release hormones to regulate neuronal function. Hormonal weights can be changed depending on the input and output values of the neuron. As it is shown, on each hidden neuron, information is regularly converted between input and output units. These neurons also provide active hormones from Hc, Hb and Ha that these parameters are modeled based on input and output values in the model training phase then it is then designed in the training process.

Figure 20.

An Overview of the Structure of EANN (V. Nourani, (2017))



In the training process, hormone bonds affect other nodal units. Figure 19 is showing that Lines and folds determine the best pathway for the hormonal and neural information movement. The output of this neuron will calculate with 3 hormones called Hc, Hb and Ha (Nourani, V. 2017).

$$Y_i = \underbrace{(\gamma_i + \sum_h \partial_{i,h} H_h)}_{1} \times f(\sum_j [\underbrace{(\beta_i + \sum_h \chi_{i,h} H_h)}_{2} \times \underbrace{(\alpha_{i,j} + \sum_h \Phi_{i,j,k} H_h) X_{i,j}}_{3} + \underbrace{(\mu_i + \sum_h \psi_{i,h} H_h)}_{4}]) \quad (20)$$

The weights applied to the actuator function are listed in the first section. This comprises both the nerve's steady weight and the hormone's dynamic weight.

The weight applied to the sum function is shown in Section 2, while the weight applied to xij is shown in Section 3. Section 4 shows the sum function's tendencies. The synthetic hormone is resembling formula 3.21.

$$H_h = \sum_i H_{i.h} \quad (h = a, b, c) \quad (21)$$

Sharing overall hormonal levels (Hh) must control by factors.

$$H_{i,h} = glandity_{i,h} \times Y_i \tag{22}$$

So that the glendithic factor should calibrate somehow in the training EANN phase which Provide sufficient levels of hormone to the tubers. There may be plans to activate Hh hormone levels Based on input samples like applying the average input values to the training sample (Nourani, V. 2017).

Evaluation criteria

In the models themselves, whole of the data have used to control and evaluate the model. Analyzes such as the root mean square error (RMSE) are used to build confidence in the model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - C_i)^2}{N}} \tag{23}$$

In relation 23, N represents the number of samples, C_i is the calculated variables, O_i is the measured variables.

The coefficient of determination (DC) as a dimensionless coefficient is used to trust all the models used in this research. The formula for this analysis is shown in Equation24.

$$DC = 1 - \frac{\sum_{i=1}^{N}(O_i - C_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{24}$$

In relation 24, N represents the number of samples, C_i is the calculated variables, O_i is the measured variables and $\bar{O}$ is the average of the observations.

The model's success is measured by the correlation between output (DC) and target; the correlation coefficient is a statistical tool for determining the type and degree of link between two quantitative variables. One of the criteria for determining the connection between two variables is the correlation coefficient. The correlation coefficient shows the link's severity as well as the type of relationship (Direct or reverse). This rate can range from 1 to -1, and it is equal to zero if there is no connection between two variables. In addition, the results of other similar research can be used for the validation of the forthcoming research (Nourani, V. 2017).

$$\operatorname{corr}(X,Y) = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{25}$$

Where E stands for the mathematical hope operator, “cov” for covariance, “corr” for Pearson correlation, and Sigma stands for standard deviation.

CHAPTER 4
Results and Discussion

To perform modeling and find effective inputs, correlation coefficients were performed between different inputs. Then the results of different models on pollutants are obtained. In the next step, the comparison of the results obtained from the models is presented and finally the general summary of the results is discussed. The modeling of the Emotional Artificial Neural Network has been studied with more precision and description, because it is the most basic, newest and most innovative modeling of this research.

Pollutants correlation coefficients and sensitivity analysis

In this study, the correlation coefficients (CC) between each of the pollutants and other statistical parameters, namely humidity and temperature, were calculated. CC has been used in this dissertation to select effective inputs. Which is generated by combining all of the input statistical parameters for each pollutant's simulation. Different parameters are put in the sensitivity analysis. Aside from that, the model's sensitivity to the parameters has been tested. Table 3 shows the results of correlation coefficients between the research's input parameters.

Table 3.

Correlation Coefficient Between the Modeling of Inputs

	TEM	HUM	NO2	PM 2.5	PM 10	SO2
TEM	1	-0.62	-0.64	-0.47	-0.33	-0.26
HUM	-0.62	1	0.60	-0.40	0.24	0.51
NO2	-0.64	0.60	1	-	-	-
PM 2.5	-0.47	-0.40	-	1	-	-
PM 10	-0.33	0.24	-	-	1	-
SO2	-0.26	0.51	-	-	-	1

As it is shown in Table 3, the highest correlation coefficient is between temperature and NO pollutant and is close to -0.7. In addition, the lowest value is the correlation coefficient between PM10 and humidity, which shows the value of -0.24.

It should also be mentioned that, according to the sensitivity study, the humidity parameter has the highest sensitivity (29%) and the temperature parameter has the lowest sensitivity (7%). Based on traffic characteristics, it was determined that modeling is more accurate during vacations owing to lower pollution levels. Modeling performs better during the day than at night in terms of time. In the summer, on the other hand, there is a higher performance, which may be ascribed to less traffic caused by the closure of schools and educational facilities.

Results of Feedforward Neural Network (FFNN)

FFNN model is one of the self-correlated models that allows non-linear control of time series autocorrelation. The type of neural network used in FFNN model is due to prediction of Perceptron, which contains 3 layers (input layer, hidden layer and output layer). This type of neural network model with reverse diffusion algorithm, was described in the previous chapter.

The right selection of input variables, as well as the correct adjustment of programme parameters such as stimulus functions, the number of intermediate neurons, and the number of network training repetitions, define the output of an FFNN model (Epoch). To determine the optimum FFNN structure, researchers employed trial and error as well as sensitivity analysis. The goal of this trial and error is to figure out how many hidden layer neurons there are and how many rounds the algorithm takes to construct the model. The mentioned process is being implemented by using NNtool in Matlab software or by writing a relevant code. It's worth noting that a limited number of training repetitions might result in insufficient training, while a high number of repetitions can result in network retention throughout the training phase. As a result, the ideal number of replications should be evaluated in order to ensure that the model's quality is adequate for both training and testing. In this study, the number of replications was determined through trial and error in the range of 150 to 250. Due to its high convergence power, the Alonberg-Marquardt algorithm has been used to teach neural networks. In which, the theory is described in Chapter 3. The network training process stops when the error rate between the test data starts to increase. In the following, FFNN modeling of each pollutant will be explained separately.

Different hidden neuron and different epochs were used to extract from the best result and best model, the best result is shown in Table 4.2. This table shows the coefficient of determination (DC) and root mean square error (RMSE) in an attempt to obtain the best model of artificial neural network. As can be seen, for example, by selecting 30 hidden neurons and 100 epochs, the best result is obtained for the NO2 pollutant.

Table 4.

Modeling Results of FFNN For the Pollutants of London

pollutants	Time scale	Input variables	Number of hidden neurons	Epoch	DC		RMSE	
					Train	verification	Train	verification
NO2	Time of the day per month (4 hours in a day in a month)	TEM, HUM, Lag1, DHI	3	100	0.78	0.72	0.06	0.07
PM2.5			6	60	0.71	0.66	0.07	0.08
PM10			5	55	0.68	0.60	0.08	0.08
SO2			6	60	0.77	0.70	0.06	0.07

As can be seen in Table 4, FFNN modeling was able to model NO2 Pollutants with the DC percentage of 75. This figure is different for PM2.5, which is 70%. Having said that, PM10 and SO2 have modeled with the percentage of 65 and just under 75, respectively. The reason of having accurate result for the NO2 pollutants is due to the more accurate statistics in terms of NO2 and the parameters involved.

Results of Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS model is a type of artificial neural network model and is one of the autocorrelation models that allows nonlinear control of the time series autocorrelated component. The general principles and process of modeling with ANFIS are the same as FFNN, with the difference that the parameters of this model are slightly different from the previous model. In modeling by ANFS, there are two important points that should be considered, the first is the structure of ANFIS (type and number of membership functions) the second is the number of ANFIS training repetitions. A minimal number of training repetitions, similar to neural networks, can lead to incomplete training, whereas a large number of repetitions can lead to model retention during the training phase. As a result, the appropriate number of replications should be examined in order to ensure that the model's quality is adequate for both training and testing. The number of repeats in the ANFIS model is set through trial and error. In this study, the fuzzy logic toolbox of MATLAB programme was employed to simulate ANFIS. In the MATLAB environment, the anfisedit command is used to invoke ANFIS. Many membership functions for fuzzy inputs are available in the MATLAB platform (such as triangular, trapezoidal, bell, Gaussian, etc.). The gaussmf and trampf membership functions were utilised to fuzzy the inputs in this study. The numbers for each input were calculated by trial and error, and the best results were highlighted.

Different hidden layers and different epochs were used to extract the best result and form the best model, the best result being shown in Table 4.3. This table shows the coefficient of determination (DC) and root mean square error (RMSEs) in an attempt to obtain the best model of adaptive neural-fuzzy inference system. As can be seen, for example, by selecting trampf, Mf4, 10 epochs, the best result is gained for SO2 pollutatnt.

Table 5.

Modeling Results of ANFIS For the Pollutants of London

	Time scale	Input	FIS producer	MF	Epoch	DC		RMSE	
						Train	Verification	Train	Verification
NO2	Time of the day per month (4 hours in a day, month)	TEM, HUM, Lag1, DHI	trampf	Mf3	11	0.58	0.53	0.08	0.09
PM2.5			gaussmf	Mf3	8	0.59	0.53	0.09	0.10
PM10			trampf	Mf4	12	0.56	0.51	0.10	0.10
SO2			trampf	Mf4	10	0.66	0.62	0.07	0.07

As can be seen in Table 5, ANFIS modeling with DC was about 67% able to model PM10 pollutants. This figure is about 55% for PM2.5 and about 65% and 55% for SO2 and NO2. These entire have less DC and more RMSE compared to FFNN modeling. The reason for the better performance of FFNN than ANFIS can be explained in the high number of layers of the ANFIS model, which because in the present modeling, the number of inputs is also very high, with a small error RMSE at the beginning, a high final nonlinear error is obtained.

Results of Emotional Artificial Neural Network

The EANN model was used as another Marco-Finn model with an AI-based approach with the same input and output structure and only a change in the number of hidden layers and an epoch repetition. For each of the contaminants, the results obtained from the EANN modeling are expected to be better than the FFNN and ANFIS modeling results; because with the addition of the emotional (hormonal) part of modeling to the previous FFNN model, the accuracy and performance of the model should be improved. In fact, a similar modeling of FFNN occurs in this part, with the difference that hormones have been added to the modeling and its amount is determined by trial and error and improves the results. It can be explained that in FFNN modeling, hormones play the role of the middle layer, and with a small number of latent neurons, desirable results can be achieved.

Different hidden layers, different hormones and different epochs were used to extract the best result and form the best model. The best result is shown in Table 4.4. This table shows the coefficient of determination (DC) and root mean square error (RMSEs) in an attempt to obtain the best model of artificial sensory neural network. As can be seen, for example, by selecting 1 hidden layer, 4 hormones and 98 epoch, the best result is obtained for SO2 pollutants. In addition, the consistency of the model results with the observed values for SO2 contaminants can be seen in Figure 22 . Also for PM10, NO2 and PM2.5 pollutants in Figures 21,23 and 24, the results can be seen in comparison with the observed values.

Table 6.

Modeling Results of EANN For the Pollutants of London

	Time scale	Input variables	Hormones	Number of hidden neurons	Epoch	DC		RMSE	
						Train	verification	Train	verification
NO2	Time of the day per month (4 hours in a day in a month)	TEM, HUM, Lag1, DHI	7	3	12	0.84	0.81	0.05	0.06
PM2.5			5	2	20	0.78	0.74	0.07	0.07
PM10			4	2	23	0.82	0.78	0.06	0.06
SO2			4	1	98	0.89	0.84	0.05	0.05

As can be seen in Table 6, FFNN modeling was able to model SO2 Pollutants with the approximate percentage of DC of 90. This figure is different for PM2.5, which is 75%. Having said that, PM10 and NO2 have modeled with the percentage of 80 and just under 85, respectively. The reason of having accurate result for the SO2 pollutants is due to the more accurate statistics in terms of SO2 and the parameters involved. EANN modeling system have a bigger DC rate when compare with FFNN modeling system. That is to say, it is occurring because of existing of Hormones in EANN modeling. Therefore, that, with the decreasing in the number of hidden neurons and place to their space, cause to gives a better results.

Figure 21.

Comparison of EANN Modeling Results with Observational Time Series of NO2 A) All-Time series B) Selected Range

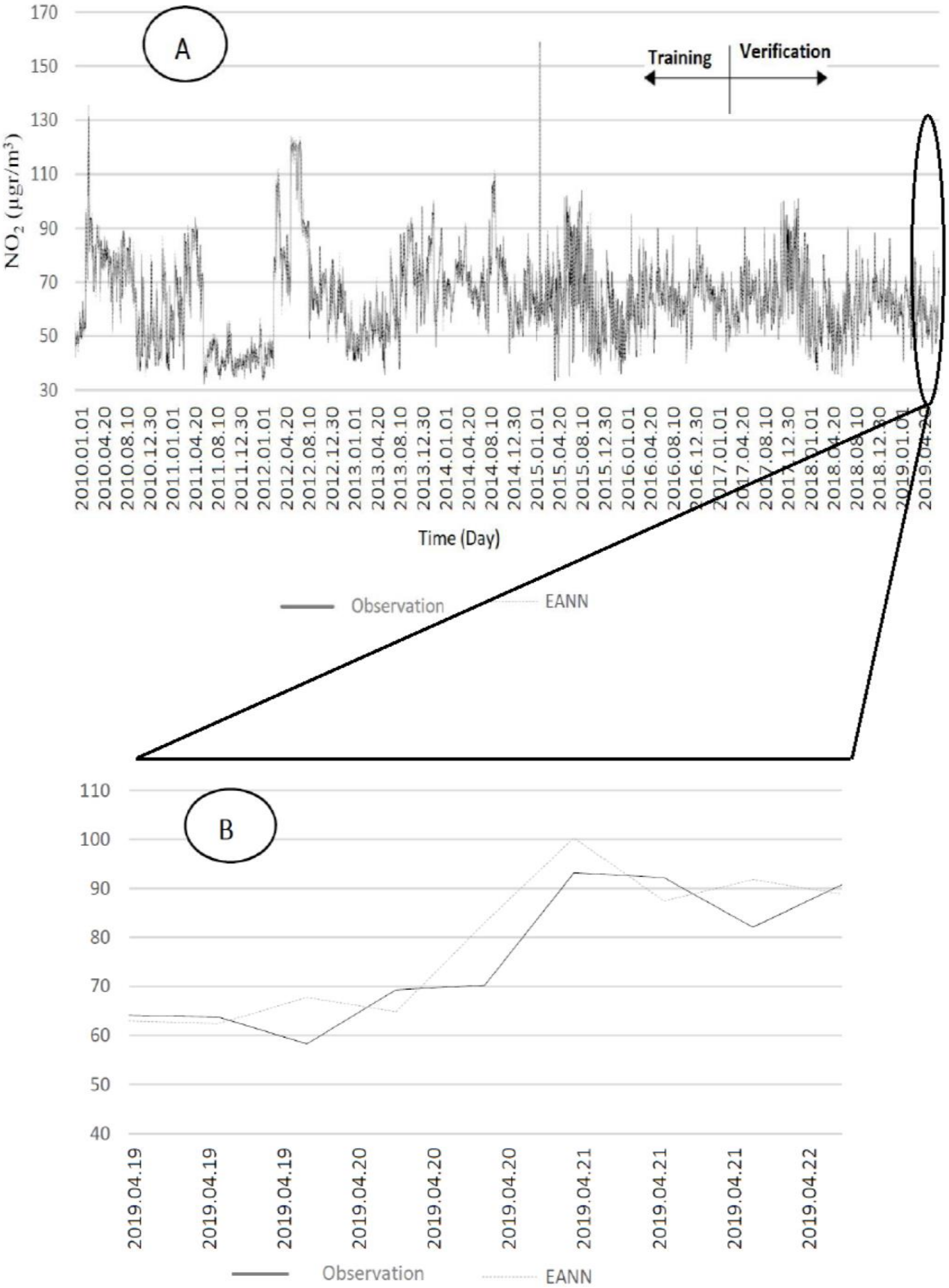


Figure 22.

Comparison of EANN Modeling Results with Observational Time Series of SO2 A) All-Time series B) Selected Range

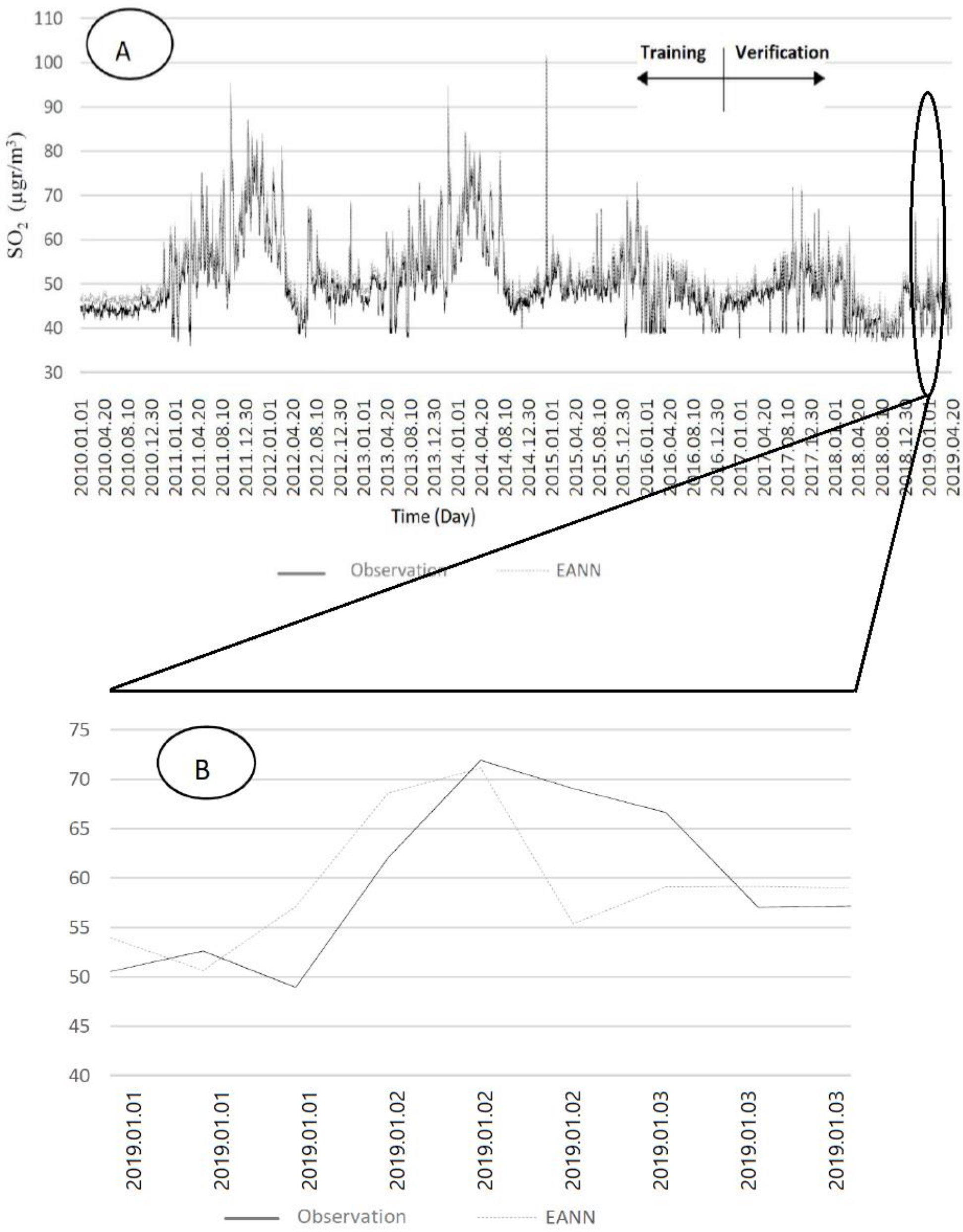


Figure 23.

Comparison of EANN Modeling Results with Observational Time Series of PM2.5 A) All-Time series B) Selected Range

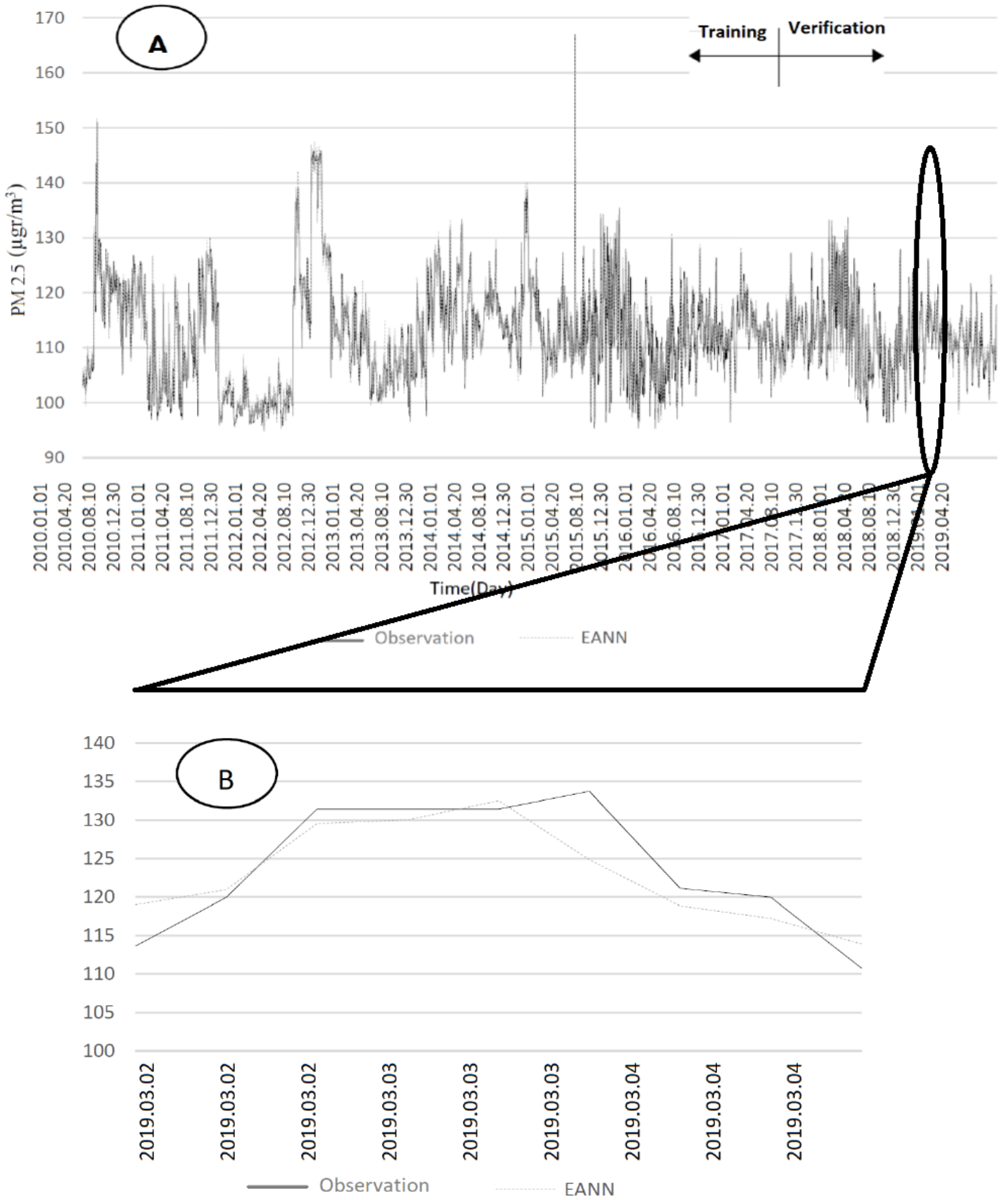
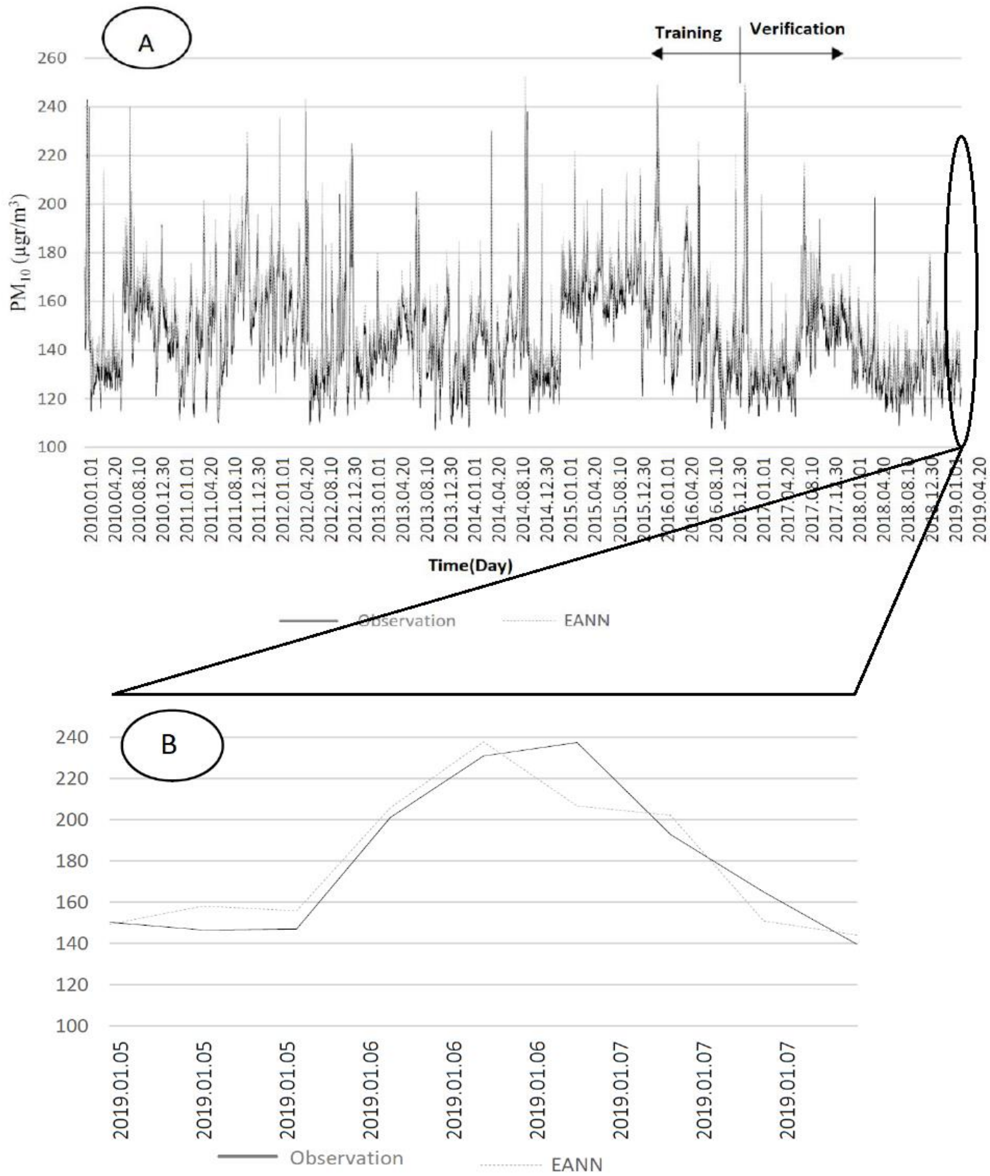


Figure 24

Comparison of EANN Modeling Results with Observational Time Series of PM10 A) All-Time series B) Selected Range



As can be seen from Figures 21 to 25, EANN modeling performs pollutants modeling significantly well and can be mentioned the best modeling among the models performed in this research.

Scatter plots have shown between Figures 25 and 28. X-axis is as the target and y-axis is as the calculated output. The scatter-plots that go along with it show the degree of correlation between the output and the objective. Each point reflects the quantity of output for the goal value it corresponds to. The correlation between the output and the goal SO2 and NO2 is 89 percent and 84 percent, respectively, as illustrated in Figures 4.5 and 4.6, indicating a good value and a satisfactory outcome. In addition, by the measured correlation, 82% and 78% are belonged to PM10 and PM2.5, respectively.

Figure 25.

EANN model scatter plot between anticipated and real SO2

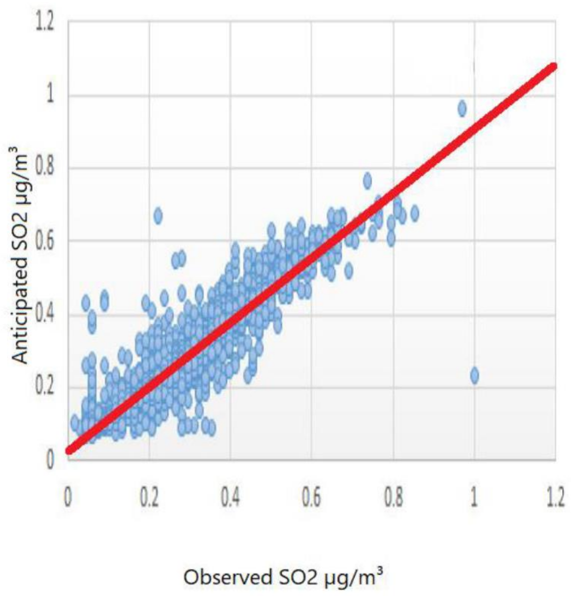


Figure 26.

EANN model scatter plot between anticipated and real NO2

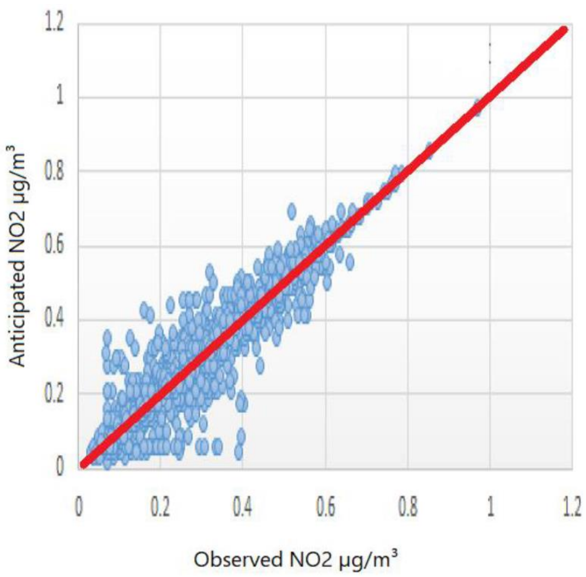


Figure 27.

EANN model scatter plot between anticipated and real PM10

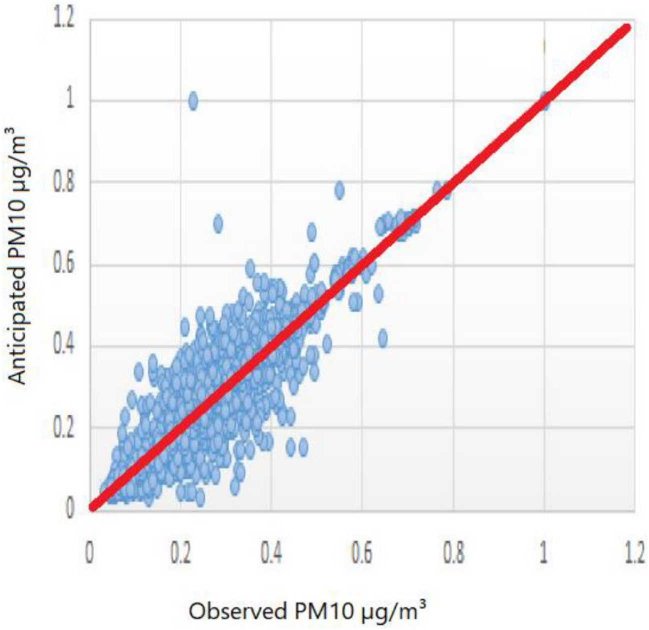
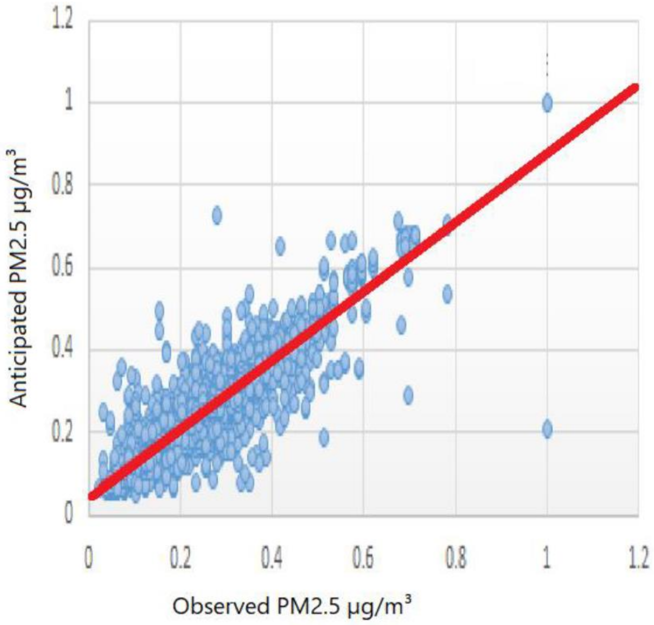


Figure 28.

EANN model scatter plot between anticipated and real PM2.5



CHAPTER V
Discussion

In this section, the results obtained from FFNN, ANFIS and EANN modeling for each of the pollutants are compared based on the DC and RMSE parameters of the modeling to determine the percentage of performance improvement by using each relative models to each other, then based on the results, and their comparison, discussion, will be Taken place.

In the case of NO2 pollutants, based on DC validation and RMSE value, FFNN modeling performed 19% better than ANFIS. EANN also performed 10% and 28% better than FFNN and ANFIS, respectively.

In the case of PM2.5 pollutants, based on DC validation and RMSE value, FFNN modeling performed 13% better than ANFIS. EANN also performed 8% and 21% better than FFNN and ANFIS, respectively.

In the case of PM10 pollutants, based on DC validation and RMSE value, FFNN modeling performed 9% better than ANFIS. EANN also performed 18% and 27% better than FFNN and ANFIS, respectively.

In the case of SO2 pollutants, based on DC validation and RMSE value, FFNN modeling performed 8% better than ANFIS. EANN also performed 14% and 22% better than FFNN and ANFIS, respectively.

As you have seen the results show that ANFIS is not as much reliable for the field of Air Quality in the region of London, even in somewhat cases the results are shown opposite and by the consideration by detail, came out that the results for NO2 and SO2, despite the fact that, the pollutants NO2 and SO2 have reached to the most effective pollutants, ANFIS shows that these pollutants are not as much effective. Having said that, after attention to my results and study the other articles and the last 3 ISI articles of Prof. Vahid Nourani, I have experienced ANFIS is not reliable as much for the field of Air Quality in the region like London. In addition, the reason for the superiority of EANN can be explained by the increase of hormones. In which, Hormones can decrease the number of Hidden Neurons that leads to having a better performance in the modeling system. Having said that, utilizing Hormones is like using two hands instead of one hand for doing a job.

One of the utilitarian feature that has applied in this Thesis is using hours and days instead of the number of cars or factories in traffic pollutants data. Since reaching to the exact number of cars is not much possible, the statistics of some hours have utilized. That is to say, focus on the results on some hours have somewhat benefits. For instance, the amount of pollutants is negligible at night when it compare with the middle of the day based on the data we have. Therefore, for better results, this innovation has used.

In terms of the inputs, two kind of index, which is Temperature and Humidity, has used. maybe a question will be come up that why these two factor has used? It should be noted that, the effects of temperature and humidity is noticeable in London and have most impact on air quality. Using of the mentioned two factor leads to gaining a better result. For instance, why precipitation is not as much operational? The effect of temperature and humidity are visible all the time. However, precipitation has occurred only a few days in a month. Alternatively, regarding the factor of wind, some reason indicate that utilizing wind is not expressed such an impressive data. Having said that, our data has gained from different three station in different three situations. So that, as you know, the route of wind can be various and cannot be reliable. If the research has considered briefly and not specific to the exact situations, it could be possible.

The temperature has a big impact on the movement of air. So in the following, air pollution have moved respectively. The air close to the surface of the ground have a warmer air compare to the air existing further up in the troposphere, since when the sun is shining to the surface of the ground, the energy from the sun has absorbed by the surface of Earth. The warmer and low-weight air rises from the surface. On the other hand, the cooler and weighty air sink in the troposphere. That is to say, the pollutants are moved from the surface of the ground to the upper altitudes by this role. The exhaust coming from vehicles, smokestacks can be felt intensely in the cold weather. Does it means that the amount of pollutants are more in the winter, or the vapor that it comes out from the vehicles are more visible? Both of them is right. As you know the amount of emission of the factories remain constantly over the year. However, in some cases in winter, somwhat pollutants is developing. Particulate matter and carbon monoxide pollutants have an upper trend by burning woods during the winter months or warming cars up in order to getting preventive action of being freezing and so on. Generally, the warm air causes to lift the pollutants away from the ground. Instead, the layers of warm air play a role as a gate for retain the cold weather at the surface of the ground. This fact establishes a thermal inversion. In which, when a layer of warm weather coming above to the cold air, it is formed. Warm reversals are more common over cities where cold air gets caught in mountains or valleys.

Many people feels not comfortable in the existence of humidity and hot weather, when they doing physical sports. In addition, humidity have a big impact on air pollution in ways that turns the weather to a harmful type of it for human and its respiratory system. Humidity of the air is a kind of gaseous water this means that a combination of vapor and dry air is humidity. The degree of humidity is directly depends on how hot or cold the temperature is. Higher humidity makes the weather harmful and an increase in the rate of toxic particulars even cause to create dust in our houses. Because of existence of bacterial and viral organisms in higher rate of humidity, respiratory infections will be developed. Also, the low rate of humidity can cause to airborne germs. Humidity can alter the appearance of particular matter in the air. By the rising the rate of humidity, the size of particular matter will be increased. Eventually, it becomes too heavy and starts to fall, instead of going to the troposphere.

Nitrogen Dioxide (NO2) is a form of nitrogen oxides (NOx) group. At first, NO2 comes out from burning fuels. In which, the emission of cars, off-road equipment, and power plants forms NO2. By coming out, the harmful effects of that is starting. After combining with water, it turns into acid rain. Besides, the nitric particulars make the air hazardous and hazy.

PM stands for particulate matter that it consist of liquid droplets and solid particles in the air. Somewhat particles that can be seen by the naked eyes such as dust, soot and smoke, which are large enough to seeing it. The rest of it that are too small can be detected by microscope. The source of these pollutants can be widely different. Some are outpoured from the sites of construction directly or smokestacks, unpaved roads, and so on. Particular matters can be caused serious problem in health. The liquid droplets or solid particles of the pollutants less than 10 micrometers in diameter can permeate to our lungs and bloodstream. In addition, the particles less than 2.5 micrometers in diameter can be the most dangerous thing for the health of human.

The combustion of fossil fuels by power plants and other industrial facilities is the most major producer of SO2 in the atmosphere. Industrial operations such as mineral mining, natural sources such as volcanoes, and locomotives, ships, and other vehicles and heavy equipment that use sulfur-rich fuel are all smaller producers of SO2. As a result of SO2 emissions, high SO2 concentrations in the air almost always result in the formation of additional sulphur oxides (SOx). Small particles can form when SOx reacts with other chemicals in the environment. Particulate matter (PM) pollution is caused by these particles. Small particles can enter deep into the lungs and cause health issues if there are enough of them. SO2 and other sulphur oxides can combine with other chemicals in the atmosphere to generate microscopic particles that decrease visibility (haze) in several parts of the UK, including many of our beloved national parks and wilderness areas.

CHAPTER VI
Conclusion and Recommendations

The aim of the present study was to predict air pollutants in London by two models of Feedforward Neural Network (FFNN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Emotional Artificial Neural Network (EANN). In this study, temperature, humidity, pollutants data and traffic-pollution-sources data were used as input. Meteorological information includes temperature and humidity; air pollutants in London include particulate matter less than 2.5 microns, particulate matter less than 10 microns, nitrogen dioxide and sulfur dioxide. In addition, traffic data with approximate proportions, including hours entered, Time of the day per month has implemented. Then the time series of input variables were plotted and the correlation coefficient of the variables was calculated. Based on DC validation and RMSE, the Feedforward Neural Network (FFNN) modeling performed better than the Adaptive Neural-Fuzzy Inference System (ANFIS), and the Emotional Artificial Neural Network (EANN) performed better than the Feedforward Neural Network. The reason for the better functioning of FFNN than the ANFIS can be found in the artificial intelligence specific to the FFNN and also the reason for the superiority of the EANN can be explained by the addition of hormone. Also, the control of the obtained results was performed using the root mean square of the errors, which in all cases, reasonable and reliable results were obtained.It should be noted that these models are black boxes and especially the physical (environmental) features of the city of London are not considered in the modeling. Therefore, the modeling of this research can be used in modeling pollutants in other cities and regions.

Recommendations

I) In this dissertation, for modeling air pollutants, meteorological parameters, equivalent traffic data and also the values of pollutants were used, which it is suggested to use the geographical parameters of the city such as elevation and other related parameters because such parameters It can be also affected in hot weather and cold weather, etc.

II) Considering the fact that the time series of pollutants often have seasonal changes (such as temperature inversion, etc.) and on the other hand, artificial intelligence models are sensitive to these sudden changes in the data process, other suggestions that can be made, use The input is organized by the data clustering method, because the clustering method homogenizes the data and reduces model fluctuations and thus reduces a lot of changes in the data.

III) One of the concerns of artificial intelligence models is its capacity and ability to predict the next few steps. The high capacity of Artificial Intelligent models to predict a next step has been proven in many fields and many published studies on FFNN have used a next step prediction. As a result, modeling a few steps later not only one-step is another suggestion that can be considered in future work.

IV) In this research, the average data of 3 meteorological stations in London have been used for the amounts of pollutants. In the next research, each of these station or stations in the city center or stations close to the city's industries can be modeled spatially using GIS facilities and examined them.

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Appendices

Appendix A

Turnitin Similarity Report

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12/06/2021

Prof. Dr. Huseyin Gokcekus

Appendix B

Ethical confirmation

Date:12.06.2021

To the Graduate School of Applied Sciences

My name is Rouzbeh Jafari Tofighi with student number 20182670. The research project titled "FORCASTING MEGACITY POLLUTANTS USING CLASSICS AND EMOTIONAL ARTIFICIAL NEURAL NETWORKS" has been evaluated. Since the researcher will not collect primary data from humans, animals, plants or earth, this project does not need to go through the ethics committee.

Signatures

Title: Professor

Name: Prof.Dr. Huseyin Gokcekus

Role in the Research Project: Supervisor ....

Title: Professor

Name: Prof. Dr. Vahid Nourani

Role in the Research Project: Co-Supervisor ....

Note: If the research project is a thesis, the supervisor and the co-supervisor (if applicable) should fill this form and send it to the relevant graduate school. If this is an independent project by a faculty member, they should fill this form themselves.