International Journal of Environmental Trends (IJENT)
http://dergipark.gov.tr/ijent

International Journal of Environmental Trends (IJENT)

2025; 9 (1),33-47
ISSN: 2602-4160

Turkish JournalPark ACADEMIC

Research Article

Evaluation and Prediction of Air Quality in Kayseri Organized Industrial Zone by Using ANNs

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Received
05 December 2024

Accepted
10 May 2025

Keywords
Air Quality
ANNs
PM2.5
PM10
SO_2

Abstract

Industrial activities cause air pollution such as motor vehicle traffic, construction activities, energy production, as well as waste management. Air pollution has diverse adverse effects on human health and environmental health. Therefore, the environmental monitoring of air quality is very important for public health and environmental health protection. Such monitoring is assisted easily by artificial intelligence (AI). AI technologies such as artificial neural networks (ANNs) have started to receive wider attention in recent times for monitoring and modeling air pollution. Because these technologies facilitate easier and more accurate data processing and analysis which, therefore, aids in the estimation of air pollution levels.

In this research, data relating to PM2.5, PM10 and SO_2 levels collected from January 1, 2020 to November 1, 2024 at the air quality monitoring station in Kayseri Organized Industrial Zone are analyzed. The study is conducted in two stage. The first part deals with factors affecting the observations in this long period. The second part involves using a multilayer perceptron (MLP) artificial neural network model to predict the PM2.5, PM10 and SO_2 levels. The data covering the period from January 1, 2020 to January 1, 2024 were applied to train the artificial intelligence model for modeling purposes, while those from January 1, 2024 to November 1, 2024 were employed for the validation of the model. In this step, ANNs can identify and exclude missing or unusual measurements. It was determined that the MLP model can be used for air pollution modelling. In addition, the consistency of the model was discussed and climatic data can be included to improve it.

KAYSERİ ORGANİZE SANAYİ BÖLGESİ'NDE YAPAY SİNİR AĞLARI KULLANILARAK HAVA KALİTESİNİN DEĞERLENDİRİLMESİ VE TAHMİNİ

Anahtar Kelimeler
Hava Kalitesi
YSA
PM2.5
PM10
SO_2

Özet

Endüstriyel faaliyetler, motorlu taşıt trafiği, inşaat faaliyetleri, enerji üretimi ve atık yönetimi gibi hava kirliliğine neden olur. Hava kirliliğinin insan sağlığı ve çevre sağlığı üzerinde çeşitli olumsuz etkileri vardır. Bu nedenle, hava kalitesinin çevresel izlenmesi halk sağlığı ve çevre sağlığının korunması için çok önemlidir. Bu tür izleme, yapay zeka (AI) tarafından kolayca desteklenir. Yapay sinir ağları (YSA) gibi AI teknolojileri, son zamanlarda hava kirliliğini izlemek ve modellemek için daha geniş ilgi görmeye başlamıştır. Çünkü bu teknolojiler daha kolay ve daha doğru veri işleme ve analizini kolaylaştırır ve bu nedenle hava kirliliği seviyelerinin tahmin edilmesine yardımcı olur.

Bu araştırmada, Kayseri Organize Sanayi Bölgesi'ndeki hava kalitesi izleme istasyonunda 1 Ocak 2020 ile 1 Kasım 2024 tarihleri arasında toplanan PM2.5, PM10 ve SO_2 seviyelerine ilişkin veriler analiz edilmiştir. Çalışma iki aşamada yürütülmüştür. İlk bölüm, bu uzun dönemde gözlemleri etkileyen faktörleri ele almaktadır. İkinci bölüm, PM2.5, PM10 ve SO_2 seviyelerini tahmin etmek için çok katmanlı algılayıcı (MLP) yapay sinir ağı modelinin kullanılmasını içermektedir. 1 Ocak 2020 ile 1 Ocak 2024 arasındaki dönemi kapsayan veriler, yapay zeka modelini modelleme amaçları doğrultusunda eğitmek için uygulanırken, 1 Ocak 2024 ile 1 Kasım 2024 arasındaki veriler modelin doğrulanması için kullanıldı. Bu adımda, YSA'lar eksik veya sıra dışı ölçümleri belirleyebilir ve hariç tutabilir. MLP modelinin hava kirliliği modellemesi için kullanılabileceği belirlendi. Ayrıca, modelin tutarlılığı tartışıldı ve onu iyileştirmek için iklim verileri dahil edilebilir.

International Journal of Environmental Trends, *9* (1), 33-47. DOI: not now possible

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INTRODUCTION

Improving air quality can greatly contribute to human health and the environment. Air pollution means the presence of harmful substances in the atmosphere. It is one of the most responsible factors for poor health. Air pollution usually originates from many pollutants, including particulate matter (PM2.5 and PM10) and sulfur dioxide (SO_2). These parameters are considered main pollutants in the atmosphere. PM2.5 and PM10 are fine particles that penetrate deep into the respiratory system and have an effect to human health [1]. The World Health Organization (WHO) advises that exposure to such particles can lead to certain lung and heart diseases, including hastening premature death [2]. Such harmful effects of PM2.5 are compounded by continuous exposure and have become a serious public health problem. SO_2 is a product gas of burning fossil fuel burning [3], which is closely related to respiratory disorders such as bronchitis and irritation of the respiratory system itself [4]. SO_2 in the atmosphere causes acid rain, which damages the ecosystem and negatively affects agriculture, water resources and biodiversity [5].

The integration of artificial intelligence (AI) technologies like machine learning models or artificial neural networks (ANNs) can also provide potential solutions to monitoring and control of air pollution. Real-time analysis of enormous data by AI would yield accurate predictions concerning pollution that would benefit the development of accurate models of proactive decision-making. This advanced technology would be beneficial to air quality management and sustainable solutions for it. In many parts of a very polluted area, for example, industrial zones, real-time monitoring and prediction applications of AI for air quality would yield better environmental sustainability, together with more accurate and effective interventions.

In the last few years, ANNs and other AI techniques have entered into air quality prediction and management [6-13]. An advanced tool which uses ANNs is very advantageous that it can even derive some prediction from analysis of complex datasets with a very high degree of precision [14]. Moreover, AI techniques are expected to be increasingly adopted to enhance the accuracy of predictions and simplify the decision-making process in various environmental research fields. Such techniques could advantageously learn from historical data [15, 16] and discover multidimensional relationships [17, 18] that are nonlinear and therefore, are very suitable for addressing the complex dynamics of air pollution.

The benefits of AI techniques in air quality prediction are the ability to model complex relationships, handle large datasets, deliver fast and reliable predictions and adapt to new conditions. ANNs in particular are adept at processing and analysing complex data, allowing them to predict future levels of air pollution based on past trends. For instance, a study by Agarwal et al. [18] demonstrated that ANNs could effectively estimate concentrations of pollutants like PM10, PM2.5, NO_2 and O_3. Their model achieved strong performance, with correlation coefficients for pollutants ranging from 0.79–0.88 for some and 0.49–0.68 for others. Similarly, Jiang et al. [19] utilized a multilayer perceptron (MLP) architecture in their ANN model, emphasizing that at least one year of data is necessary for successful predictions. They also found that the simpler structure of the MLP model delivered better results. In another study, Jairi et al. [20] applied MLP models to predict concentrations of pollutants such as PM2.5, PM10, NO_2, SO_2, CO and O_3. Their findings highlighted that the model significantly enhanced forecasting accuracy, especially in scenarios with limited labeled data. These studies underscore the transformative potential of AI and ANNs in improving air quality prediction and environmental management. Monitoring and predicting pollutant levels in industrial zones are crucial for effective environmental management and protecting public health. Research in this field has demonstrated that ANNs are a reliable and efficient method for air quality prediction, offering valuable tools for managing air pollution in industrial areas.

The aim of the study is to evaluate the potential of ANNs for air quality prediction and management. In the first stage of this study, the levels and causes of PM2.5, PM10 and SO_2 emissions measured in Kayseri Organized Industrial Zone were evaluated with cause and effect relationship. In the second stage, PM2.5, PM10 and SO_2 emissions were modeled with ANNs and the consistency of the model was emphasized.

MATERIAL AND METHOD

The measurement results belong to an air quality monitoring station in the organized industrial zone of Kayseri (in Türkiye) and are listed on the website of the Turkish National Air Quality Monitoring Network [21]. The parameters investigated in this study are PM2.5, PM10 and SO_2 emissions, measured between 1/1/2020 and 1/11/2024.

Multilayer perceptron (MLP) was used to develop the ANNs model in this study. In data analysis and decision-making process, this kind of ANNs models facilitates the processing of complex data [22, 23] while using the Python programming language. The collaboration between Python and ANN-based tools enables a more efficient and accurate modelling process for air pollution prediction. The reason for using python software in the study is that it is a widely used language for data analysis and machine learning. It is also suitable for developing projects such as environmental pollution prediction. AI techniques have also emerged as valuable tools for understanding and predicting complex data models, owing to the scikit-learn, pandas and numpy libraries. This enables a better understanding of the behaviour of environment variables. The data were first analysed for missing values and outliers. Missing data were removed from the data set by a cleaning process in MLP. All air quality parameters were converted into numbers. A training set created from data from 1 January 2020 to 1 January 2024 was used to train the model. Data after 1 January 2024 was used to create the test set. Therefore, the measurement data is divided into two groups, the training set has 1349 measurement results and the test set has 306 measurement results.

MLP consists of an input layer, one or more hidden layers and an output layer. In each layer, neurons perform calculations through activation functions. In the model, PM2.5 and PM10 values had been first entered as input variables and SO_2 values were used as target variables. To enhance the overall performance of the version, the input facts have been standardized by way of using standardscaler. This manner guarantees that each one enter variables are evaluated on the same scale. After PM2.5 and PM10 modelling, PM2.5 and PM10 values had been used as independent variables for SO_2 modelling. SO_2 was set as the established variable and made the goal of the model to estimate the effect of PM2.5 and PM10. The impartial variables were standardized the usage of standardscaler, as they may have unique scales. This manner increased the efficiency of the version's mastering procedure through remodelling the mean of both parameters to 0 and the same old deviation to 1. The formulas of the MLP can presented in Eqs. (1) and (2):

$$H_j = \delta \cdot \left(\sum_{i=1}^{n} \omega_{ij} \cdot X_i + b_j\right) \qquad \text{Eq. (1)}$$

In this formula,

H_j : Output of hidden neuron j,

σ : Activation function,

ω_{ij} : The weight of input i to neuron j,

b_j : Bias for neuron j,

n : Number of entries.

Prediction of the output neuron:

$$Y = \delta \cdot \left(\sum_{j=1}^{m} \omega_j \cdot H_j + b\right) \qquad \text{Eq. (2)}$$

Y : Estimated value,

ω_j : Weights from the hidden layer to the output neuron,

b : Bias for output neuron,

m : Number of neurons in the hidden layer.

In this study, the configuration of the MLP model included a total of 150 neurons (100 in the first hidden layer and 50 in the second hidden layer). The learning process of the model was performed by optimizing the weights and biases. The success of the model is evaluated by predictions on training and test data. Performance measures include mean squared error (MSE), mean absolute error (MAE) and coefficient of determination (R^2). MSE is calculated by averaging the squares of the differences between the predicted values and the actual values, as given in Eq. (3).

$$\boldsymbol{MSE} = \frac{1}{n}\sum_{i=1}^{n} y_i - y_i^{l} \qquad \text{Eq. (3)}$$

In this formula,

n: Total number of samples in the data set,

y_i: Actual values,

y^l_i: Estimated values.

MAE is calculated by averaging the absolute differences between predicted values and actual values, as shown in Eq. (4):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - y_i^{ı} | \qquad \text{Eq. (4)}$$

R^2 indicates how much of the variance in the data set is explained by the model. It takes a value between 0 and 1 and is calculated by the following Eq. (5):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i^{ı})}{\sum_{i=1}^{n}(y_i - y^{i})} \qquad \text{Eq. (5)}$$

In this formula,

y_i: Actual values,

$y^{ı}_i$: Estimated values.

RESULT AND DISCUSSION

Air Quality Assessment

In this study, firstly, long-term air quality data in Kayseri Organized Industrial Zone (measured between 1.1.2020 and 1.11.2024) were analyzed to evaluate the PM2.5, PM10 and SO_2 air pollution parameters. In the second stage, these data were utilized to model air quality prediction using ANNs. The data shown in Figures 1, 2 and 3 provide a comprehensive perspective of the impacts of industrial activities and other factors on air quality.

The results, presented in Figures 1 and 2, show that PM2.5 and PM10 levels increase significantly during periods of intense industrial activity. Industrial facilities can emit large amounts of PM into the atmosphere during processes such as metal processing, textiles, chemicals and other industrial activities. These emissions arise from operations like material processing, cutting and grinding. The combustion of fossil fuels (coal, diesel, oil) is also a significant source of PM emissions, especially when low-quality fuels are used. Construction activities can also cause dust (PM10) and other particles to become airborne during the transportation of soil and other materials. Additionally, traffic in organized industrial zones (trucks and diesel-powered vehicles) contributes to PM emissions. Diesel vehicles can release high levels of particulate matter. In industrial areas, windy weather conditions can cause dust and other particulate matter to remain suspended in the air and spread. These particles pose a significant threat to human health, causing health problems such as respiratory disease, cardiovascular disease and lung cancer [2, 24]. Data from air quality monitoring stations show an increase in PM2.5 and PM10 levels, especially during the winter months. One of the main reasons for this increase is the effect of fossil fuels (such as low-quality coal and waste oils) used for heating and local industrial emissions.

The SO_2 levels is shown in Figure 3. It is directly related to industrial emissions and exhaust emissions from transportation vehicles. Many industrial facilities rely on fossil fuels like coal, oil and natural gas for energy production. The combustion of fossil fuels, especially coal and oil, which contains a high sulphur content, is a primary source of SO_2 emissions. Industrial boilers and heating systems that burn sulphur-rich fuels contribute to SO_2 emissions, particularly in colder months when heating demand is high. Moreover, industrial facilities using various chemical manufacturing processes involving sulphur compounds may also release SO_2 directly into the atmosphere. In the organized industrial zone, road vehicles are used for purposes such as transporting raw materials, shipping products and personnel coming and going to the facilities. Transportation vehicles, especially diesel-powered vehicles, produce SO_2 emissions, especially when low-quality fuel is used. Increasing SO_2 levels in the atmosphere leads to the deterioration of air quality in the region and threatens public health [18]. The release of SO_2 into the atmosphere causes sudden fluctuations in air quality and has negative impacts on ecosystems [20]. High levels of SO_2 can have devastating effects on soil and water resources by creating the conditions for acid rain [19].

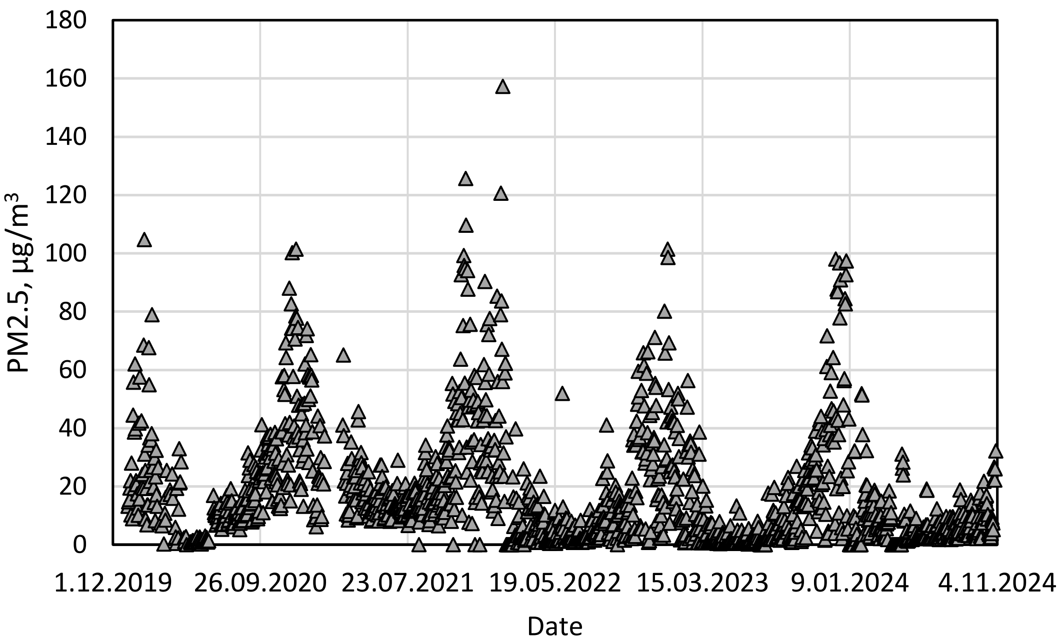

Figure 1. PM2.5 daily average concentrations measured between 1/1/2020 and 1/11/2024.

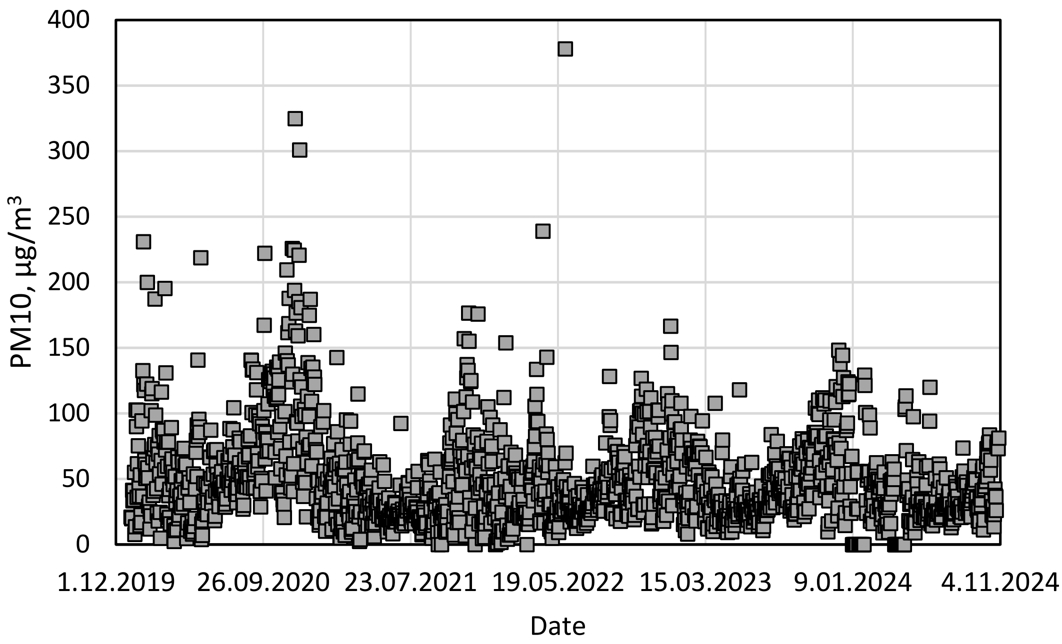

Figure 2. PM10 daily average concentrations measured between 1/1/2020 and 1/11/2024.

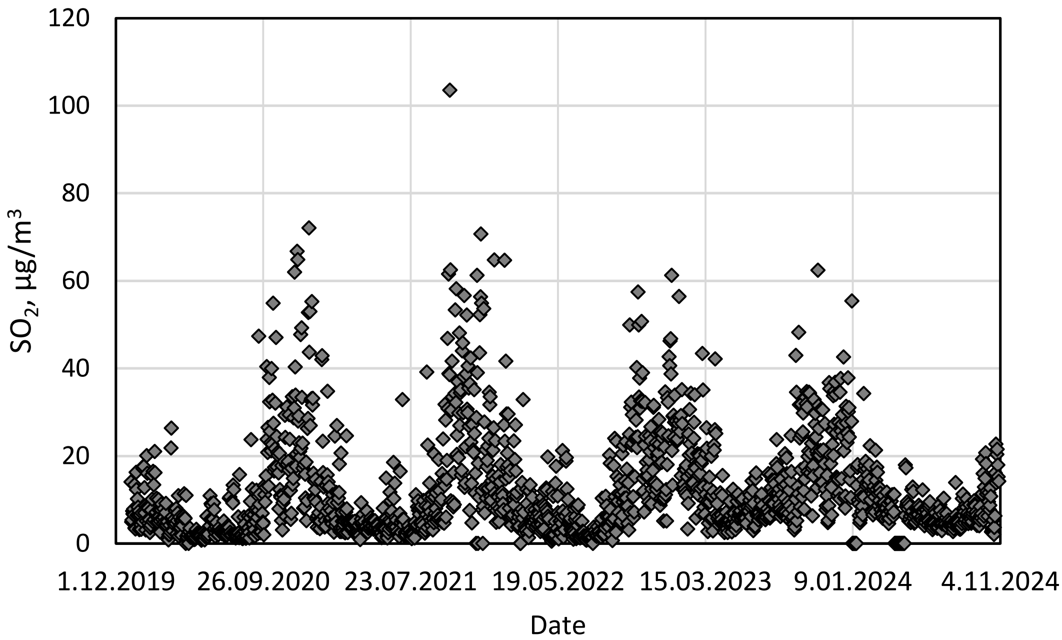

Figure 3. SO_2 daily average concentrations measured between 1/1/2020 and 1/11/2024.

The graphs show that the measurement results change significantly over time. The main reasons for these changes are the increase in industrial activities in the organized industrial zone, seasonal and climatic conditions, traffic and transportation effects and environmental management practices. The increase in industrial production in the organised industrial zone also has a direct impact on air quality parameters. The opening of new facilities and the increase in the production capacity of existing facilities also cause an increase in PM10 and SO_2 emissions. Industrial facilities may cause air pollution as a result of energy consumption and various chemical reactions during production processes [18]. In addition, the increase in the density of industrial facilities in the industrial zone leads to further deterioration of air quality. Similar findings are also found in the literature emphasizing that there is a direct relationship between emission levels and health problems in humans [24].

The impact of seasonal changes on air quality has been evident with the increase in the use of fossil fuels for heating purposes, especially in winter months. Increased energy demand in winter months has caused a significant increase in PM2.5 and PM10 levels. In addition, atmospheric stability conditions also cause pollutants to accumulate in the atmosphere. The effects of climatic factors on air quality have been widely studied in the literature and their effects have been explained [19].

Traffic density in Kayseri Organized Industrial Zone is an important factor affecting air pollution. Exhaust emissions from diesel and gasoline vehicles used in urban traffic release various pollutants into the atmosphere. Thus, exhaust emissions from motor vehicles increase PM2.5 and PM10 levels. Traffic-related air pollution increases especially during peak hours, leading to a decrease in air quality. Some studies in the literature clearly show the negative impact of urban traffic density on air quality [20].

In conclusion, air quality in Kayseri Organized Industrial Zone is constantly changing due to industrial activities, seasonal conditions and traffic emissions. Air quality fluctuations are characterized by the interactions of these factors. Regular monitoring, effective management strategies and raising environmental awareness are required to protect air quality. The effectiveness of the implemented environmental management policies and control measures plays a crucial role in the improvement or deterioration of air quality [18].

ANNs application for Pollution Prediction

In this study, an MLP-based ANN model is used to predict PM2.5, PM10 and SO_2 air quality parameters in Kayseri Organized Industrial Zone. The purpose of modelling in this study is to predict air pollution levels based on air quality data and to evaluate the accuracy of these predictions. Figures 4, 5 and 6 show the results of the MLP model. These graphs show the performance of the model.

In the predictions performed on the training and test sets, MSE is 100.42, MAE is 6.87 and R^2 is 0.37 for the training set. These results, although not perfect, show that the model is partially successful in the training process. In particular, the R^2 value of 0.37 indicates that there is uncertainty in the predictions of MLP modelling. By incorporating artificial intelligence capabilities into the modelling in the study, this model was able to improve its predictions by processing large amounts of data. Unlike the training set, MSE 15.61, MAE 2.67 and R^2 0.50 were found in the validation set. These results show that the performance of the MLP model is better in the validation set compared to the training set. This shows that the ability of the model to predict air quality parameters in general has improved and the results, especially on the test data, are more reliable.

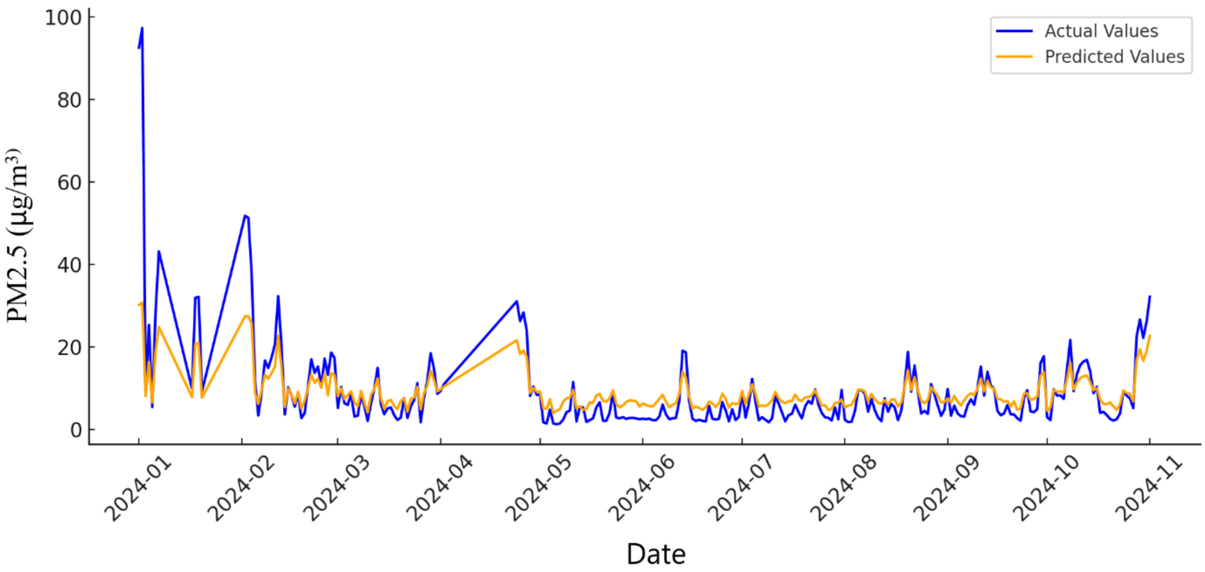

Figure 4. Real vs predicted values for PM2.5 concentrations.

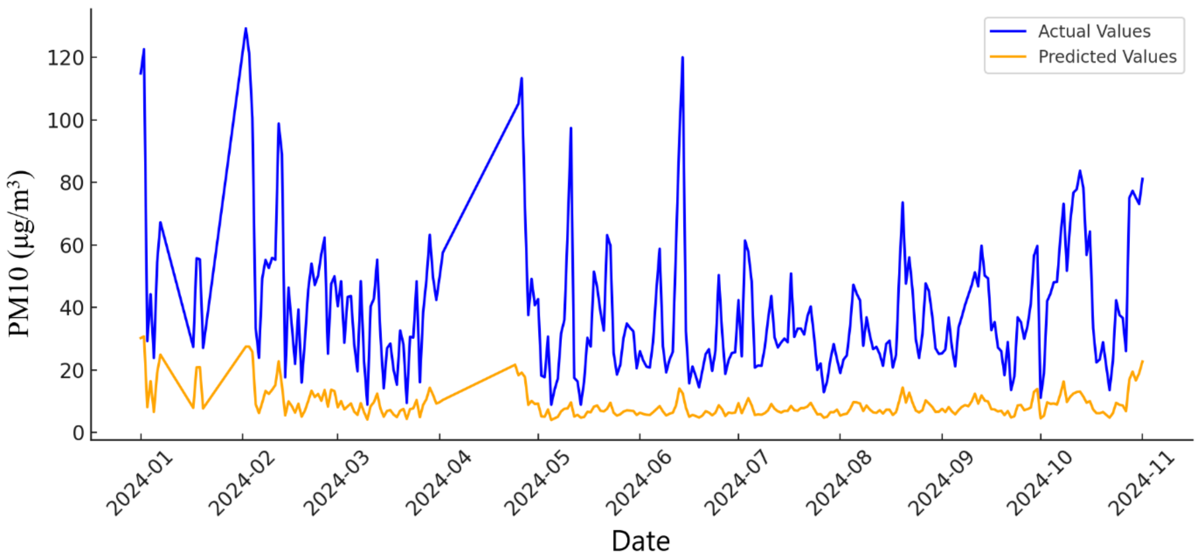

Figure 5. Real vs predicted values for PM10 concentrations.

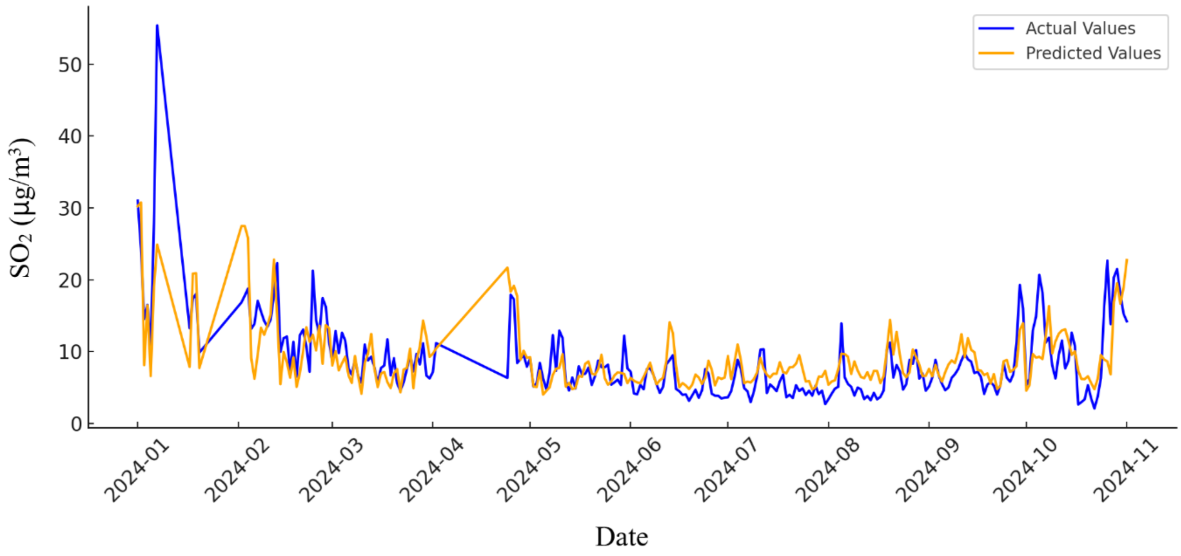

Figure 6. Real vs predicted values for SO2 concentrations.

As understood from the graphes, the model was effective in predicting the levels of PM2.5 and SO_2 emissions. There are also studies in the literature emphasizing a link between increasing PM and SO_2 levels [25]. In industrial areas, these parameters are often associated with high emission levels and lead to deterioration of air quality [2, 24].

The results of this research provide valuable information for effective monitoring and control of air quality parameters in Kayseri's organized industrial areas. To reduce air pollution, it is important to implement a comprehensive strategy to reduce industrial gas emissions. This may include improving technology to control gas emissions and introducing stricter regulations for industrial processes. Additionally, limiting the number of diesel cars on the road could significantly reduce PM and SO_2 emissions and emphasizes the need for establish guidelines that promote the use of cleaner transportation alternatives, such as electric or hybrid vehicles, in addition to promoting the transition to renewable energy such as solar and wind power. It can help reduce our dependence on fossil fuels. and help reduce all greenhouse gas emissions. Regular monitoring and evaluation of air quality data is essential to achieve cleaner air quality [20]. This proactive adjustment helps ensure that air quality management practices remain effective and appropriate in the face of with the changing environment and ultimately protect public health and increase the carrying capacity of industry.

This study clearly demonstrates the effectiveness of ANNs in predicting air quality parameters in an industrial area established in Kayseri. The model shows that ANNs can be used to analyze complex data sets and also play an important role in processing and interpreting large amounts of data. However, optimizing the learning process of the model with a larger and more accurate data set will increase the ability of the model to make more accurate predictions. This is because integrating a wider and more consistent data source provides a more robust training process for ANNs, which increases the consistency of predictions. Therefore, the use of ANN tools in pollution modelling by relevant experts offers significant advantages in terms of accelerating the modelling process and working more efficiently.

CONCLUSION

Air pollution is an important environmental and human health problem. Industrial activities in the industrial zone in Kayseri; heating cooling ventilation system factors such as power consumption and traffic density also affect air quality. These activities cause the accumulation of industrial emissions and fine particles such as PM2.5 and PM10 in the atmosphere. In terms of human health, these fine particles can cause respiratory diseases, cardiovascular disease, chronic disease, cancer and developmental disorders. High SO_2 levels in organized industrial zones can also cause respiratory problems, heart disease, skin and eye irritation. High levels of SO_2 can also cause acid rain. Soil pH decreases, agricultural production decreases and vegetation cover decreases, disrupting the balance of the ecosystem. For these reasons, monitoring and management of air quality is very important.

In this study, ANN application is preferred for modelling air pollution parameters. This is due to the effectiveness of ANN in analyzing and modelling complex data. However, the ability of ANN to efficiently deal with large datasets, the ability to learn non-linear relationships and the ability to improve model accuracy are also important advantages. ANN also plays an important role in air quality management and policy development process by improving the prediction accuracy. With these advantages, integrating ANN into air quality studies will expand the models by providing insights from scale data, improve the learning process and provide support for data analysis and decision making. In this study, the levels of PM2.5, PM10 and SO_2 emissions were modelled using ANN. The numerical results obtained in the training set as a result of modelling were calculated as MSE 100.42, MAE 6.87 and R^2 value 0.37. In the validation set, MSE was 15.61, MAE was 2.67 and R^2 value was 0.50. These results show that ANNs can be used in the estimation of air quality parameters in the organized industrial zone. It was also determined that it has the ability to improve the performance of the model through data analysis. The effectiveness of ANN can be increased by using more consistent data in air quality modelling and by including climatic factors such as wind, precipitation and humidity in the modelling.

ACKNOWLEDGMENT

The author would like to thank the Ministry of Environment, Urbanization and Climate Change of the Republic of Turkey for sharing air quality measurement results with the public through the National Air Quality Monitoring Network.

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