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Article

Analysis of PM10 Substances via Intuitionistic Fuzzy Decision-Making and Statistical Evaluation

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Abstract: Air pollution is a situation that negatively affects the health of humans and all living things in nature and causes financial damage to the environment. In the case of air pollution, harmful and foreign substances in the air reach an amount and density above normal values. Air pollution also causes climate change, which affects global warming. Particulate matter is a harmful substance that harms the health of humans and other living things, causes air pollution, increases radiation, and negatively affects cloud formation. Particulate matter is extremely small solid particles and liquid droplets suspended in the air. PM10, which is less than 10 microns in diameter, is defined as small particles that can remain in the air for a long time and settle in the respiratory tract, damaging the lungs. Many criteria affect PM10 density and changes in density. The main criteria are vehicle traffic and fuel consumption, industrialization, coal, fuel oil and wood-burning heaters, greenhouse gas impact, and unregulated urbanization. It is important to identify the underlying causes of air pollution caused by PM10. In this context, these criteria need to be evaluated to minimize the negative effects of PM10. In the study, monthly average PM10 data between 2019 and 2023 obtained from the Air Monitoring Station in Kocaeli, Türkiye are used. After determining the criteria affecting PM10, the criteria are prioritized with the Intuitionistic Fuzzy AHP (IF-AHP) method by taking expert decision-maker opinions. The proposed decision-making model aims to guide obtaining the important causes of PM10 emission in terms of danger and focusing on these causes. Additionally, PM10 data is analyzed in the context of Covid-19 and a statistical analysis is made. One-way ANOVA is used to evaluate whether there is a significant difference in the average monthly data over the years. Games-Howell test, one of the post-hoc tests, is used for differences between groups (years). The study is important in that it provides a focus on the criteria affecting PM10 with an intuitive fuzzy perspective, along with statistical analysis.

Keywords: air pollution; PM10; intuitionistic fuzzy AHP; one-way ANOVA

1. Introduction

Since air is one of the most basic elements for the vital functions of humans and many living things, “air pollution” becomes an issue that concerns all people. Increases in the concentrations of pollutants that cause air pollution also greatly affect human, living, and environmental health. According to the World Health Organization (WHO), approximately 7 million people in the world die every year due to air pollution-related causes such as lung cancer, heart disease, and acute respiratory diseases [1]. It is reported that air pollution is the cause of approximately 45 thousand preventable premature deaths every year in Türkiye [2]. It is possible to group air pollutants as gases and aerosol pollutants. Carbon monoxide (CO), nitrogen oxides (NO_x), sulfur dioxide (SO₂), and volatile organic compounds (VOCs) are the main gaseous pollutants. Particulate matter (PM10 and PM2.5) is the most dangerous fraction of aerosol pollutants due to inhalation risks. PM10 is used to refer to coarse respirable particles with an aerodynamic diameter of less than 10 µm, and PM2.5 is used to refer to fine respirable particles with an aerodynamic diameter of less than 2.5 µm [3]. Particulate matter can occur naturally, such as in volcanic eruptions, dust storms, forest fires, vegetation, and sea spray (the mixing of aerosol particles into the air by the explosion of bubbles); It can also be caused by human-made fixed and mobile structures such as vehicle exhausts, construction

and demolition operations, residential fires, especially construction sites and industrial sites. Particles can form in the atmosphere not only naturally or as a result of human activities, but also through the transformation of gas emissions such as sulfur oxide and nitrogen [4].

Türkiye, which is in the European Union (EU) membership process, has harmonized its legislation with the EU and reduced the limit values of air pollutants, bringing them to the level of the values applied in European countries. As of the beginning of 2019, the limit values for PM10 and SO2 applied in European Union countries have also come into force in Türkiye. Air quality in our cities is constantly monitored thanks to the National Air Quality Monitoring Network operated by the Türkiye Ministry of Environment and Urbanization, and the results are announced via the website and mobile application. The Ministry of Environment, Urbanization, and Climate Change has published the Türkiye Environmental Problems and Priorities Assessment Report. According to the report prepared with 2022 data; air pollution ranked first in 22 provinces of Türkiye and among the top three environmental problems in 66 provinces. It was stated that air pollution continues to increase in Türkiye [5]. Since changes in air quality need to be constantly monitored and evaluated, it is often possible to come across studies on this subject. However, when the time aspect of the work comes into play, or in other words when time passes and the work loses its currentness, the work must be repeated. The limit value set by the WHO for the PM10 pollutant is on average 25 µm/m³ (daily) and 10 µm/m³ (annual). Limit values for PM10 pollutants have been determined for Türkiye at the national level. The limit values determined for PM10 pollutants in Türkiye cover the same values in 2021, 2022, and 2023. These values are on average 50 µm/m³ (daily), 40 µm/m³ (winter period), and 40 µm/m³ (annual). All limit values are given in Table 1 [6,7].

Table 1. PM10 limit values at international and national levels.

Pollutant	Period	WHO	Türkiye National Values
PM10	Daily	25 µm/m³	50 µm/m³
	Annually	10 µm/m³	40 µm/m³
	Winter Period	-	40 µm/m³

It is important to scientifically examine the parameters affecting air pollution to monitor air pollution and minimize the effects of pollutants such as PM10. Air pollution, defined as the presence of pollutants in the atmosphere at levels and duration that may harm human health, animals, plants, natural environment, commercial and private properties, needs to be monitored, and evaluated, and its distribution and change analyzed [8,9]. There are many studies in the literature examining the parameters affecting air pollution and pollution relationships.

Eroğlu [10] aimed to determine the extent of air pollution in the Çerkezköy and Kapaklı districts of Türkiye and the natural and human factors that cause air pollution. For this purpose, measurement values of Çerkezköy Air Quality Monitoring Station between 2013 and 2023 were used. Annual average PM10, PM2.5, SO2, NO2, NOx, and NO values were measured in Çerkezköy and Kapaklı. It has been determined that the annual averages of PM10 and NOx among these pollutants are higher than the limit values of Türkiye, the European Union, and the World Health Organization. In terms of the sustainability of the human-space relationship in Çerkezköy and Kapaklı districts, taking into account the factors that cause air pollution, practices have been suggested to solve the problems. Erener et al. [11] examined the relationship between air pollution and seasonal meteorological data in Kocaeli. They made evaluations by regression analysis with daily SO2 and PM10 parameters and meteorological data such as temperature, wind direction, wind speed, relative humidity, and air pressure for 2015. Bai et al. [12] conducted a study on natural and socioeconomic factors affecting air pollution along with urban air quality monitoring data from 2015 in the Yangtze River Economic Zone. As a result of the study, they concluded that topographic, meteorological, economic development, and urbanization factors are related to air pollution. Some scientists have shown in their research that meteorological factors (temperature, precipitation, humidity, atmospheric pressure, wind speed, etc.) have a significant impact on air pollution [13,14]. Jiang et al. [15] concluded in their study that the topographic structure prevents the clustering and dispersion of

pollutants, and it was also revealed that as the population and income level increase, factors such as fossil fuel use, increase in the number of vehicles, urbanization, and industrialization increase, causing pollutant emissions to increase, and therefore these factors affect air pollution. Lin and Wang [16] stated that air pollution is significantly dependent on energy consumption, industrialization, and technological developments in China. Two different methods are used to evaluate air pollution: deterministic methods and statistical methods. Although deterministic methods are a method that models physical and chemical processes such as discharge, accumulation, or transfer processes of pollutants using meteorological, emission, and chemistry models, the accuracy of these methods varies depending on the quality and scale of the data used and it takes a long time to apply these methods with big data. The importance of statistical methods, which compensate for the shortcomings and weaknesses of deterministic methods, is increasing in studies [17]. Statistical methods have also been used in the literature, especially in studies involving the PM10 pollutant. Some of these methods include estimation and examine the relationship between variables, and some include statistical analysis according to significance levels [18–21].

The Covid-19 pandemic has had serious negative effects on human health and the world economy; however, limiting social and economic activities also mediated the reduction of air pollution [22]. Because the main source of air pollution is anthropogenic activities [23]. It appears that the measures taken have reduced the volume of these activities to a large extent. For example, during the quarantine, mobility decreased by approximately 50% in Italy and 79% in France [24,25]. Particularly with travel restrictions and flexible working opportunities, the density in the transportation sector, which constitutes approximately one-quarter of total greenhouse gas emissions and is considered the main cause of air pollution in cities, has been greatly reduced [26]. The decrease in emission sources of air pollutants has played an encouraging role in research conducted to determine changes in air quality.

In this study, the criteria affecting PM10 values are examined in detail the criterion weights are obtained from the Intuitionistic Fuzzy AHP perspective and the criterion importance ranking was reached. In this context, the criterion or criteria affecting PM10 that will be focused on and evaluated are discussed from an intuitive fuzzy decision-making perspective. This point is the motivation for the study as it fills the gap in the literature. In addition to this decision analysis, a statistical evaluation was also presented using 5-year PM10 values covering the COVID-19 period in Kocaeli, Türkiye. Determination of whether there was a significant difference between the average data was evaluated by one-way analysis of variance. In the second phase of the study, materials and methods are given. The third phase covers the findings. The fourth phase contains discussion and conclusions.

2. Materials and Methods

The flow diagram of this study process is given in Figure 1.

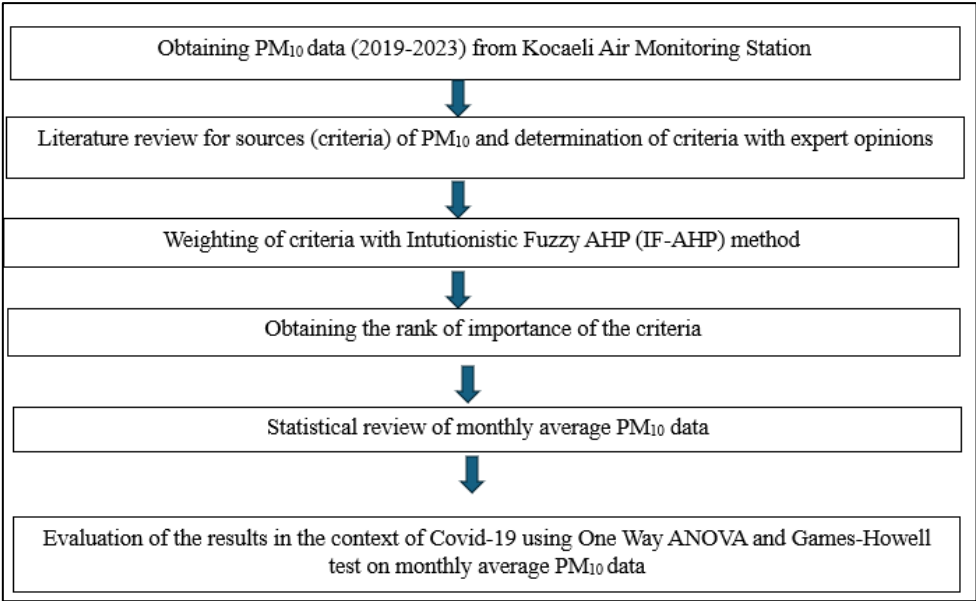


Figure 1. Flowchart of study process.

2.1. Study Area and Data

Kocaeli province is located in the Marmara Region of Türkiye. Figure 2 shows the location of Kocaeli [27]. Kocaeli is the 10th most populous city in Türkiye and according to 2023 TURKSTAT data, its population is 2.102.907 people and its area is 3626 km² [28].



Figure 2. Map of Kocaeli.

Since the negative effects of air pollution on human health are known, air quality sampling data should be collected at a certain frequency to determine the level of emissions. For this purpose, 125 air pollution surveys were conducted in 81 provinces between 2005 and 2007 by the Türkiye Ministry of Environment, Urbanization, and Climate Change to measure air pollution accurately, establish air pollution policies in all provinces, and improve the air quality of the provinces within the framework of these policies compared to the values of the previous year. A quality measurement station was established and a National Air Quality Monitoring Network was established throughout Türkiye. Sulfur dioxide (SO₂) and particulate matter (PM₁₀) parameters can be measured fully automatically in all established air pollution measurement stations, and in some additionally, nitrogenides (NO, NO₂, NO_x), carbon monoxide (CO) and ozone (O₃). Measurement data collected at measurement stations are monitored and transferred to the Ministry's Environmental Reference Laboratory Data Processing Center via GSM Modems over a special network (VPN) belonging to the Türkiye Ministry of Environment, Urbanization, and Climate Change and published simultaneously at URL-2 [29]. Verification studies are carried out by examining the data received from the stations in the form of hourly averages, and monthly and annual reports are prepared and published with the data in question. These measurements have been made continuously at stations in Kocaeli province since 1987. Air pollution parameters are measured hourly at Air Pollution Measurement Stations. There are a total of 12 measurement stations in Kocaeli province under the control of the Türkiye Ministry of Environment, Urbanization, and Climate Change [27].

Monthly average PM₁₀ data for the years 2019-2023 obtained from Kocaeli Central station are given in Table 2.

Table 2. Monthly average PM₁₀ concentration values data in Kocaeli.

Months/Year s	2019	2020	2021	2022	2023
January	59.45	43.18	44.67	39.85	49.55
February	58.4	44.53	47.74	52.45	46.42
March	51.69	45.11	38.3	51.08	34.51
April	45.47	39.39	42.58	55.93	34.2
May	58.05	39.24	37.77	40.1	30.41
June	51.42	39.51	37.68	34.81	23.16
July	40.78	31.59	40.25	29.9	33.52
August	41.98	30.73	38.91	39.89	39.31
September	45.53	38.4	37.24	39.69	29.84
October	55.55	45.54	39.74	39.22	53.85
November	78.06	39.5	63.62	55.72	42.35
December	70.07	44.72	41.82	64.02	61.02

According to Table 2, Kocaeli's annual average PM₁₀ values are 54.70; 40.12; 42.53; 45.22, and 39.85 between 2019 and 2023, respectively. The highest value of 54.70 was achieved in 2019 when the COVID-19 pandemic had not yet started. Due to restrictions around the world, the annual average PM₁₀ concentration value decreased significantly in 2020. Annual average PM₁₀ concentration value started to increase again in 2021 and 2022. In 2023, it showed a serious decrease again. It can be thought that this decrease is related to the regularization of various measures for air pollution on the agenda and the adoption of the remote working principle by most businesses due to the Covid 19 pandemic. A detailed examination of the criteria affecting PM₁₀ concentration is important in this context. In this study, the criteria affecting PM₁₀ concentration values determined by literature evaluation are weighted with Intuitionistic Fuzzy AHP by taking expert opinion. Thus, the order of importance of the criteria could be obtained from the decision-making perspective. In addition, a statistical analysis is performed on the actual PM₁₀ values, and whether there is a significant difference between the average PM₁₀ values in the context of Covid 19 is evaluated by One-Way ANOVA.

In the following sections, Intuitionistic Fuzzy AHP and One-Way ANOVA methodology are given.

2.2. Intuitionistic Fuzzy AHP (IF-AHP)

The AHP method was developed by Professor Thomas L. Saaty and used for decision-making problems. AHP is a methodology based on one-to-one comparisons of the criteria and sub-criteria affecting the decision according to their degree of importance, using a binary comparison scale in any decision problem. The AHP method also aims to prioritize by distinguishing between alternative options to meet interconnected goals [30]. However, AHP cannot fully reflect the functioning of the complex human thought system. For this reason, the method has been used by many researchers in problem-solving by combining it with the fuzzy logic approach [31–33]. In the following periods, the uncertain and hesitant situations of experts and the decision environment brought about the search for heuristics in the fuzzy AHP method. By developing intuitive fuzzy set theory, this approach has been integrated with the AHP method and investigated by several researchers [34]. Abdullah and Najib [34] proposed a new heuristic fuzzy AHP with a new pairwise matching comparison matrix evaluation preference scale. This new preference scale leads to the proposal of a new consistency test for matrix evaluation using the values of the degree of hesitation. The steps of intuitionistic fuzzy AHP method presented by Abdullah and Najib are as follows:

- Step 1: A hierarchical structure is created for the decision problem.
- Step 2: Pairwise comparison matrices are created with the triangular intuitive fuzzy numbers preference scale in Table 3.

Table 3. Triangular Intuitive Fuzzy Numbers.

Comparison Preference	AHP Preference Correspondence	Triangular Intuitive Fuzzy Numbers	Opposite Triangular Intuitive Fuzzy Numbers
Equal	1	(0.02 0.18 0.8)	(0.02 0.18 0.8)
Important	2	(0.06 0.23 0.7)	(0.23 0.06 0.7)
Middle	3	(0.13 0.27 0.6)	(0.27 0.13 0.6)
Somewhat	4	(0.22 0.28 0.5)	(0.28 0.22 0.5)
Important	5	(0.33 0.27 0.4)	(0.27 0.33 0.4)
Middle	6	(0.47 0.23 0.3)	(0.23 0.47 0.3)
Very Strong	7	(0.62 0.18 0.2)	(0.18 0.62 0.2)
Important	8	(0.8 0.1 0.1)	(0.1 0.8 0.1)
Middle	9	(1 0 0)	(0 1 0)
Absolutely			
Important			

Step 3: The weights of decision makers are determined. The degree of importance of the decision maker or experts to the decision problem is also expressed by linguistic variables. Triangular intuitive fuzzy numbers defined for linguistic variables are in Table 4. $D_k(\mu_k, v_k, \tau_k)$ is the expression of the degree of importance of expertise of the decision maker “k” for the decision in terms of an intuitive fuzzy number.

Table 4. Linguistic variables and their equivalents for the importance levels of decision makers.

Linguistic Variables	Triangular Intuitive Fuzzy Number Correspondence
Very important	(0.90 0.05 0.05)
Important	(0.75 0.20 0.05)
Somewhat Important	(0.50 0.40 0.10)

Insignificant	(0.25 0.60 0.15)
Very unimportant	(0.10 0.80 0.10)

The weight of k expert is calculated using Equation (1) [35].

$$\lambda_k = \frac{\mu_k + \tau_k \left(\frac{\mu_k}{\mu_k + v_k} \right)}{\sum_{k=1}^l (\mu_k + \tau_k \left(\frac{\mu_k}{\mu_k + v_k} \right))} \quad (1)$$

Where,

$$\sum_{k=1}^l \lambda_k = 1, \quad k = (1, 2, \dots, l)$$

Step 4: The collective intuitive fuzzy decision matrix based on the decision maker's opinion is created using the intuitive fuzzy weighted average (IFWA) operator developed by Xu [36].

The combination form of the IFWA operator is given in Equation (2), where $R^{(k)} = (r_{ij}^{(k)})_{m \times n}$ is the intuitive fuzzy decision matrix of the k. decision maker and $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$ is the weight of all decision-makers.

$$r_{ij} = IFWA_{\lambda}(r_{ij}^{(1)}, r_{ij}^{(2)}, \dots, r_{ij}^{(l)}) = (\lambda_1 r_{ij}^{(1)} (+) \lambda_2 r_{ij}^{(2)} (+) \dots (+) \lambda_l r_{ij}^{(l)}) \quad (2)$$

$$r_{ij} = (1 - \prod_{k=1}^l (1 - \mu_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^l (v_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^l (1 - \mu_{ij}^{(k)})^{\lambda_k} - \prod_{k=1}^l (v_{ij}^{(k)})^{\lambda_k})$$

From here to $r_{ij} = (\mu_{ij}, v_{ij}, \tau_{ij})$;

It is expressed as;

$$\mu_{ij} = 1 - \prod_{k=1}^l (1 - \mu_{ij}^{(k)})^{\lambda_k}$$

$$v_{ij} = \prod_{k=1}^l (v_{ij}^{(k)})^{\lambda_k}$$

$$\tau_{ij} = \prod_{k=1}^l (1 - \mu_{ij}^{(k)})^{\lambda_k} - \prod_{k=1}^l (v_{ij}^{(k)})^{\lambda_k}$$

Step 5: The consistency ratio (CR) is calculated for the collective heuristic fuzzy decision matrix. Since the bulk intuitionistic fuzzy matrix contains the $\tau(x)$ value, which is the hesitation value of triangular intuitionistic fuzzy numbers, a new method is presented for calculating the consistency ratio (Abdullah and Najib, 2014). Random index values (RI) were taken from Table 5 presented by Saaty in the standard AHP method [37]. According to the new method presented, CR is calculated by the equation in Equation (3). ($\lambda_{max} - n$) in Equation (3) is the average of the $\tau(x)$ values in the aggregated intuitive fuzzy matrix of each criterion. The value of n is the size of the matrix.

Table 5. RI Values.

n	1-2	3	4	5	6	7	8	9
RI	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

$$CR = \frac{(\lambda_{max} - n)/n - 1}{RI} \quad (3)$$

The matrix is confirmed to be consistent if the CR value does not exceed 0.10. If this value is greater than 0.10, there is an inconsistent decision matrix and, in this case, it is necessary to reconstruct the comparison matrices.

Step 6: The intuitive fuzzy entropy weights of the aggregated weighted intuitive fuzzy decision matrix are calculated with the equation given in Equation (4) and the final weights are calculated with the equation in Equation (5). Afterwards, final criterion weights can be reached by taking arithmetic averages.

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Step 6: The intuitive fuzzy entropy weights of the aggregated weighted intuitive fuzzy decision matrix are calculated with the equation given in Eq. (4) and the final weights are calculated with the equation in Equation (5). Afterwards, final criterion weights can be reached by taking arithmetic averages.

$$\bar{w}_i = -\frac{1}{n \ln 2} [\mu_i \ln \mu_i + v_i \ln v_i - (1 - \tau_i) \ln(1 - \tau_i) - \tau_i \ln 2] \quad (4)$$

$$w_i = \frac{1-\bar{w}_i}{n-\sum_{j=1}^n \bar{w}_j}, \quad \sum_{j=1}^n w_i = 1$$

(5)

Some of the criteria in the literature are examined to determine the criteria affecting PM10 concentration and weight them with IF-AHP [38]. The criteria determined within the scope of this study are given in Table 6.

Table 6. Criteria affecting PM10 concentration values.

Criteria affecting PM10 concentration values	Criteria No	Reference
Climatic Features	C1	[39,40]
Density of Industrial Facilities	C2	[10]
Population Growth	C3	[41]
Unplanned Urbanization	C4	[42]
Lack of Green Area	C5	[43]
Topographic Structure	C6	[44]
Motor Vehicles Emission	C7	[10]

Climatic Features (C1): The climate of a region affects the distribution of PM10 substances in the atmosphere [45]. In recent years, the relationship between air quality and meteorological conditions in cities has been the subject of research [46]. Basic climatic features such as temperature, humidity, wind speed, and pressure have a positive and negative effect on PM10 values [47]. Many studies have been conducted in the literature determining the effect of meteorological parameters on PM10 concentrations. In these studies, it was determined that there was a relationship between PM10 level and meteorological conditions [48].

Density of Industrial Facilities (C2): Pollutants are released into the atmosphere when the fuel used to obtain the energy needed in industrial facilities such as factories, power plants, combustion plants, and industrial facilities is burned. In addition, the concentration of PM10 in the air increases as a result of the burning of solid waste in furnaces and open areas [49].

Population Growth (C3): Population growth and development are rapidly changing the environment. Due to rapid population growth and increasing industrialization and urbanization, damages such as climate change, difficulty in accessing clean water, air pollution, increase in hazardous waste, deforestation, and desertification occur. It is known that the PM10 rate increases in areas with high population density [50].

Unplanned Urbanization (C4): Unplanned urbanization along with increasing energy use, the use of coal with high sulfur content in heating, the destruction of nature, and the negative impact on the climate have made air pollution and the increase in PM10 levels an important problem, especially in big cities [51].

Lack of Green Area (C5): Urban green areas have many important and even vital functions, especially in terms of ecological, economic, social, and planning [52]. However, infrastructure systems must support ecosystem functions. The function of reducing and balancing air pollution is one of these important functions. The most important role of green areas in reducing air pollution is their ability to absorb particulate matter in the air. The decrease in green areas increases the PM10 rate in the air [53].

Topographic Structure (C6): The unsuitable topographic features of the settlements have negative effects on air quality [54]. The topography of the regions affects the distribution of air pollution in the atmosphere. Topographic differences in the city also cause spatial differences in air pollution [55]. Settlements built without taking into account the topographic characteristics of the areas where cities are established further increase the existing air pollution. In regions with basin geomorphology surrounded by elevations, the amount of PM10 and its residence time in the environment are high. In cases where the topographic features of cities prevent wind flow, PM10 pollutants cannot disperse in the air [56].

Motor Vehicle Emission (C7): High levels of engine emissions occur due to low levels of engine technology, the lack of a comprehensive vehicle emissions inspection and maintenance program, as

well as poor enforcement of vehicle emissions requirements. Toxic hydrocarbons and organic oxygenates, carbon monoxide, nitrogen oxides, and soot particles are released from motor vehicle exhaust, and the PM10 rate also increases [38].

2.3. One Way ANOVA

The concept of analysis of variance used in statistics is the general name of a group method that includes many statistical methods. The simplest form of variance analysis is a one-way analysis of variance (One-way ANOVA). As with other tests, some prerequisites must be met in the application of this test. These conditions are that the dependent variable consists of quantitative data and the homogeneity of group variances. One-way ANOVA is used to analyze how independent variables interact with each other and the effect of this interaction on the dependent variable [57]. Multiple comparison post-hoc tests are divided into two groups as shown in Table 7, according to equal or different variance approaches.

Table 7. Post-hoc tests using according to variance homogeneity.

Tests using according to the equal variance theory	Tests using according to different variance theory
✓ LSD (fishcer’s significant difterince test)	✓ Tamhane Test
✓ Bonferroni Test	✓ Dunnet T3 Test
✓ Tukey HSD Test	✓ Games-Howell Test
✓ Scheffe Test	✓ Dunnet-C Test
✓ Duncan Test	
✓ Dunnet Test	
✓ Waller-Duncan Test	

In the variance homogeneity analysis results, it is said that there is a significant difference between the groups when the Sig. (p) value is less than 0.05. If the Sig. value is less than 0.05, it is necessary to find out which groups this difference is between using tests in Table 7.

The next phase includes the findings and analysis results.

3. Findings and Analysis Results

3.1. Findings of IF-AHP

According to the flow chart in Fig. 1, expert opinions (decision-makers: DMs) are taken to weigh the criteria, and the IF-AHP methodology was applied. Intuitive triangular fuzzy numbers in Table 4 are used when determining the importance weights of DMs in the decision process. In this study, there are 5 DMs in the decision process. DM1 and DM2: environmental engineers, DM3 and DM4: chemical engineers and DM5 industrial engineers. The calculated weights of DMs are given in Table 8.

Table 8. Weights of DMs for decision process.

DMs	Triangular Intuitive Fuzzy Number	λk (Weights)
DM1	(0.9 0.05 0.05)	0.235
DM2	(0.9 0.05 0.05)	0.235
DM3	(0.75 0.2 0.05)	0.196
DM4	(0.75 0.2 0.05)	0.196
DM5	(0.5 0.4 0.1)	0.138

The consistency rates in DMs matrices obtained using the formulation in Step 4 of the IF-AHP methodology are as follows. DM1:0.07 ; DM2:0.07 ; DM3:0.03 ; DM4:0.04 ; DM5:0.03. Since these ratios are lower than 0.10, the process is meaningful.

The final weights obtained from the aggregated intuitive fuzzy matrix obtained using the formulations in the IF-AHP methodology are given in Table 9.

Table 9. Final weights of criteria.

Criteria	Final Weights
C1	0.139
C2	0.148
C3	0.143
C4	0.142
C5	0.142
C6	0.144
C7	0.143

According to Table 9, the criterion with the highest importance weight is determined as C2: density of industrial facilities. The criterion with the lowest level of importance is the C1: climatic features. The importance level ranking of the criteria is obtained as C2>C6>C3=C7>C4=C5>C1.

3.2. Statistical Analysis and Findings of One-Way ANOVA

Statistical descriptives for Kocaeli's monthly average PM10 concentration values in Table 2 are calculated via the SPSS package program. The findings obtained are given in Table 10.

Table 10. Statistical descriptives for Kocaeli's monthly average PM10 concentration values.

Year	N	Mean	Std. Deviation	Std. Error	Max
2019	12	54.704	11.179	3.227	78.06
2020	12	40.120	4.956	1.431	45.54
2021	12	42.527	7.356	2.123	63.62
2022	12	45.222	10.261	2.962	64.02
2023	12	39.845	11.104	3.205	61.02
Total	60	44.483	10.534	1.360	78.06

According to Table 10, the highest mean PM10 concentration value data (54.704) belongs to 2019. The lowest mean value is calculated for 2023 (39.845). The minimum standard deviation for monthly data is calculated for 2020 (4.956), while the highest standard deviation is for 2019 (11.179).

The first restriction decisions in Türkiye due to the COVID-19 pandemic were taken on March 12, 2020. The first curfews were imposed on 10-12 April 2020. In this context, while the COVID-19 pandemic had no impact in Türkiye, as in the rest of the world, in 2019, the social, environmental, and material effects of the COVID-19 pandemic have been rapidly felt since 2020. To examine the environmental impact in detail over the years, One-way ANOVA analysis was conducted for the data in Table 2. For this, firstly, variance homogeneity was tested. The results of the variance homogeneity test are given in Table 11.

Table 11. Test of Homogeneity of Variances.

Levene Statistic	df1	df2	Sig.
2.754	4	55	0.037

Since the Sig. Value (0.037) in Table 11 is less than 0.05, the established variance homogeneity hypothesis is rejected, and it is determined that the variance is not homogeneous between the groups. The results of the One Way ANOVA test applied to the data are given in Table 12.

Table 12. Findings of One-Way ANOVA.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1792.703	4	448.176	5.184	0.001
Within Groups	4754.615	55	86.448		
Total	6547.318	59			

According to the findings in Table 12, the hypothesis that there is no significant difference between year groups is rejected because the Sig. Value (0.001) is less than 0.05. In other words, there is a significant difference between years for Kocaeli's PM10 concentration values.

To determine whether there is a significant difference between which years, the Games-Howell Post-Hoc test given in Table 7, which is used in cases where there is no homogeneity of variance, is applied. The findings obtained as a result of the Games-Howell test are given in Table 13.

Table 13. Findings of the Games-Howell test.

Dependent Variable: kocaeli_pm10						
Games-Howell						
(I) Time	(J) Time	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
2019	2020	14.58417*	3.53016	.007	3.6981	25.4703
	2021	12.17750*	3.86314	.037	.5615	23.7935
	2022	9.48250	4.38049	.230	-3.5224	22.4874
	2023	14.85917*	4.54867	.026	1.3633	28.3550
2020	2019	-14.58417*	3.53016	.007	-25.4703	-3.6981
	2021	-2.40667	2.56043	.878	-10.0953	5.2820
	2022	-5.10167	3.28947	.547	-15.1894	4.9861
	2023	.27500	3.51032	1.000	-10.5452	11.0952
2021	2019	-12.17750*	3.86314	.037	-23.7935	-.5615
	2020	2.40667	2.56043	.878	-5.2820	10.0953
	2022	-2.69500	3.64451	.944	-13.6036	8.2136
	2023	2.68167	3.84501	.955	-8.8754	14.2387
2022	2019	-9.48250	4.38049	.230	-22.4874	3.5224
	2020	5.10167	3.28947	.547	-4.9861	15.1894
	2021	2.69500	3.64451	.944	-8.2136	13.6036
	2023	5.37667	4.36451	.733	-7.5796	18.3329
2023	2019	-14.85917*	4.54867	.026	-28.3550	-1.3633
	2020	-.27500	3.51032	1.000	-11.0952	10.5452
	2021	-2.68167	3.84501	.955	-14.2387	8.8754
	2022	-5.37667	4.36451	.733	-18.3329	7.5796

*. The mean difference is significant at the 0.05 level.

According to the Sig. and mean difference values obtained in Table 13 and written in red, there is a significant difference between 2019-2020, 2019-2021, and 2019-2023 for Kocaeli's PM10 concentration values.

4. Conclusions

In this study, PM10 substance is analyzed with decision methodology and statistical evaluations for Kocaeli province, which is located in the north of Türkiye's Marmara region and is one of the most important industrial cities. The criteria affecting PM10 levels in Kocaeli city center are determined by literature review and expert opinion. The IF-AHP method is used for criterion weighting. According to the results obtained, the criterion with the highest importance is determined as C2: density of industrial facilities. The criterion that has the least impact on PM10 levels is C1: climatic features. In

addition, the changes in PM10 levels between 2019 and 2023, covering the pandemic period, are examined with statistical analysis. Although significant decreases in the levels of air pollutants are observed in Europe and other regions during the pandemic period, as a result of reduced outdoor activities, transportation, and even industrial activities due to quarantine and restriction periods, these changes are not permanent. Looking at the center of Kocaeli, the highest average PM10 level was obtained in 2019, when pandemic-related restrictions had not yet occurred. The PM10 concentration value started to increase significantly in 2020 and 2021 and 2022. This increase may indicate that heavy restrictions and measures are starting to lose their effectiveness. When this situation is associated with the results obtained with IF-AHP, effects such as decisions to work remotely or restricting production in industrial facilities may have caused changes. Surprisingly, the average value reached its lowest level in 2023. The impact of this situation may be shown as the impact of the strain on economic levels on industrial centers, but it may also be related to the fact that some measures developed during the Covid 19 period have become permanent shortly. When looking at the One Way ANOVA test results, there is a significant difference between the average monthly PM10 level groups for years. This difference exists for the years 2019-2020, 2019-2021 and 2019-2023. Accordingly, it can be said that the harmful effects of air pollution and PM10 in 2022 are similar to the monthly average levels in 2019. The motivation and innovation point of this study is that it can provide inferences to decision-makers and policy-makers through decision analysis and statistical analysis.

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