Secure Systems Design and Technology Development. Veliko Tarnovo, Bulgaria
Proceedings of the International Scientific Conference, 2026. Volume III, 341-347

Application of Fuzzy Logic in the Prediction of Air Pollution in Berlin, Germany

Desislava Velinova
Development of C4I System
Bulgarian Defence Institute
"Prof. Tsvetan Lazarov"
Sofia, Bulgaria
velinova.desislava@gmail.com

***Abstract*— Air pollution is the presence of harmful substances in the atmosphere that can adversely impact human health and other living organisms. In urban environments such as Berlin, air pollution—particularly from traffic emissions and industrial activities—continues to be a significant concern. The Air Quality Index (AQI) is commonly used to represent the level of air quality in a given area, based on the average concentrations of pollutants including particulate matter (PM_{10} and $PM_{2,5}$), ozone (O_3), carbon dioxide (CO_2), sulphur dioxide (SO_2), and nitrogen dioxide (NO_2). Accurate prediction of AQI values is crucial for mitigating the negative effects of air pollution on both the environment and public health. This paper proposes a model for AQI prediction using a fuzzy data. By applying fuzzy sets and fuzzy logic techniques, an approach is presented to handle inaccurate, incomplete, or subjective data, to achieve more reliable and robust air quality assessments.**

Keywords*— *Air pollution, Air quality index (AQI), Fuzzy Inference System (FIS), Fuzzy Logic

I. INTRODUCTION

In recent years, the development of industry and transportation has improved human life, but it has also led to increased environmental pollution, especially air pollution. Air pollution is defined as presence of harmful substances in the atmosphere that adversely affect human health, ecosystems, and even the climate. It arises from both human-related activities – such as transportation emissions, industry, energy production, burning fossil fuels, agricultural practices, and waste burning - and natural sources, including wildfires, volcanic activity, dust storms, and pollen. Some of the most important pollutants include:

- Particulate matter (PM_{10} and $PM_{2.5}$): tiny particles that can enter the lungs and bloodstream
- Ozone (O_3): a gas that forms when pollutants react in sunlight
- Nitrogen dioxide (NO_2): mainly from traffic and industry
- Sulfur dioxide (SO_2): from burning coal and oil
- Carbon monoxide (CO): from incomplete combustion (e.g., car engines)

Air pollution remains the most significant environmental risk factor for health in Europe. Air pollutants such as particulate matter (PM_{10} and $PM_{2.5}$), nitrogen dioxide (NO_2), and ozone (O_3) can lead to respiratory diseases (like asthma and bronchitis), cardiovascular diseases, type 2 diabetes, neurodegenerative diseases (e.g., dementia), and cancer. Fine particulate matter ($PM_{2.5}$) is especially dangerous because they can penetrate deep into the lungs and even enter the bloodstream. Sulfur dioxide (SO_2) irritates mucous membranes and can cause eye irritation and respiratory problems. Despite EU limits, pollution levels are often exceeded, making $PM_{2.5}$ a growing global concern.

Air pollution doesn't just affect humans. It contributes to climate change, causes acid rain, damaging forests and lakes, harms wildfires and crops, reduces visibility (smog).

Predicting pollution levels and taking preventive measures—such as traffic restrictions and health warnings—are key to protecting public health. Urban areas are particularly affected due to industry and traffic, while weather conditions can influence how pollution spreads, sometimes carrying it across regions. Because of this, monitoring and coordinated global action are essential.

Online ISSN 3044-7771
https://doi.org/10.68302/std2026.vol3.96

Advances in scientific research on the causes of air pollution and the development of mitigation strategies are essential for implementing effective control measures, forecasting pollution levels, and providing timely warnings to vulnerable populations when hazardous air quality conditions arise. This paper presents a model for predicting the Air Quality Index (AQI) busing a proposed Fuzzy Inference System (FIS) model. A Mamdani-based FIS was developed to evaluate AQI by considering five major input pollutants: PM_{10}, $PM2_{.5}$, NO_2, O_3 and SO_2. The second section describes the data collection process and the employed methodology. The third section presents the analysis of the results, discusses model improvements, and the key research findings.

II. Data and Methodology

Data Collection

Hourly data on particulate matter (PM_{10} and $PM_{2.5}$), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO) is collected from the monitoring station located in an urban area on Frankfurter Allee in Berlin. A total of 2160 data sets are collected from 1st January to 31st March 2026. They were obtained from the Federal Environment Agency in Germany. In this article was used only one week a hourly data set

Air quality index (AQI) Rating Scale

In Europe, air quality is monitored to protect health in accordance with the EU Ambient Air Quality Guideline (AAQD). The new European Air Quality Directive 2024/2881 introduces stricter limit values for air pollutants, which will become binding in the member states from 2030 [1].

The rating scale of the AQI status indicator consists pollutant concentrations, that are classified into five index categories from "very good" to "very poor" using threshold values as shown in Table 1. It is based on hourly average measurements of ozone (O_3), nitrogen dioxide (NO_2), particulate matter (PM_{10} and $PM_{2.5}$), and sulfur dioxide (SO_2). The values are hourly averages measured in micrograms per cubic meter (µg/m³). This measurement is based on classification made from the Federal Environment Agency in Germany [1]. These threshold values were derived based on current health studies and taking into account the recommendations of the World Health Organization (WHO) [8].

TABLE 1 AIR QUALITY INDEX (AQI) [1]

Air Quality Index (AQI)	PM_{10}	$PM_{2.5}$	O_3 (Ozone)	NO_2	SO_2
Very poor	over 90	over 50	over 240	over 100	over 100
Poor	55–90	31–50	145–240	61–100	61–100
Moderate	28–54	16–30	73–144	31–60	31–60
Good	10–27	6–15	25–72	11–30	11–30
Very Good	0–9	0–5	0–24	0–10	0–10

Data Analysis

Data analysis was performed using MATLAB, a powerful software platform equipped with numerous built-in tools for problem-solving and graphical visualization. A fuzzy inference system is a principled control system based on the fuzzy theory. The method used to predict the Air Quality Index (AQI) through a Fuzzy Inference System (FIS) consists of four main steps: (I) Fuzzification of input and output variables, (II) Fuzzy Inference, which involves selecting appropriate membership functions for both input and output variables, (III) the development of a fuzzy rule base, which defines the application of logical rules, and (IV) Defuzzification, where fuzzy results are converted into a crisp output value [6]. The overall structure of the fuzzy system is illustrated in Figure 1 [3].

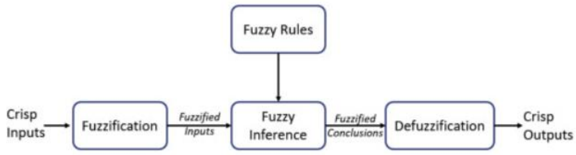

Fig. 1. Fuzzy Inference System [3]

I) Fuzzification of input and output variables

Fuzzification is the process of transforming crisp numerical values into fuzzy values. In this step, real or measured input data are interpreted as linguistic variables using appropriate membership functions. These functions represent human reasoning and uncertainty by assigning degrees of membership to each input. Both input and output variables are expressed in linguistic terms such as “Very Good,” “Good,” “Moderate,” “Poor,” and “Very Poor.

First, it was selected the system variables. The most important input variables are PM10, PM2.5, O3, NO2 and SO2. As the number of input variables in the system increases, a larger number of fuzzy rules is required to describe all possible input–output relationships. Consequently, the complexity of the system increases significantly. The input and output are taken in the form of linguistic format. For example, PM10 = (Very Good, Good, Moderate, Poor, Very Poor), PM2,5 = (Very Good, Good, Moderate, Poor, Very Poor), O3 = (Very Good, Good, Moderate, Poor, Very Poor), NO2 = (Very Good, Good, Moderate, Poor, Very Poor), SO2 = (Very Good, Good, Moderate, Poor, Very Poor. The output variable AQI = (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy).

Figure 2 shows the fuzzy inference system that consists of five inputs (PM_{10}, $PM_{2.5}$, O_3, NO_2 and SO_2) and one output which is air quality index (AQI). By using FIS editor and membership function editor from MATLAB software all the membership functions are developed.

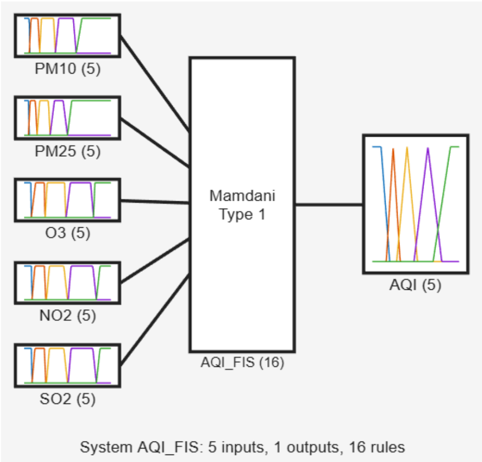

Fig. 2. AQI Determination Using Fuzzy Logic

II) Fuzzy Inference – Selection of Membership Functions for Input and Output Variables

Linguistic values are represented using fuzzy sets. Each fuzzy set is characterized by a membership function that defines the degree of belonging of an element to the set. Triangular and trapezoidal membership functions are commonly used due to their simplicity and computational efficiency. In this article, it was used trapezoidal function. Mathematically, the trapezoidal membership function is defined as follows:

$$\mu_{triangle}(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases} \qquad (1)$$

The trapezoidal membership function, shown in Equation 1, is defined by a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, where a < b < c < d.

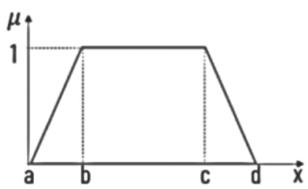

Fig. 3. Trapezoidal membership function [5]

This function is used to map linguistic values into the range [0, 1], representing the degree of membership in the fuzzy set. The membership function of input and output are represented in Figure 4 and Figure 5.

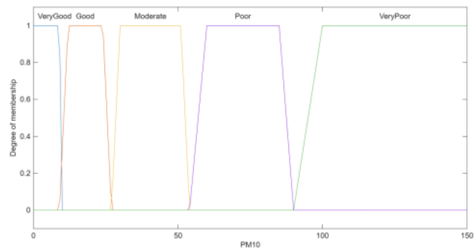

Fig. 4(a). Membership function of PM_{10}

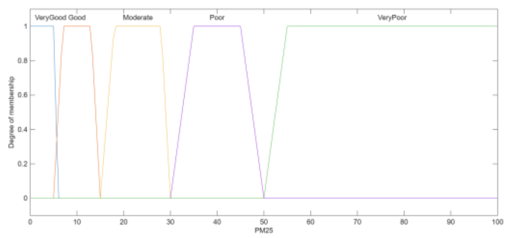

Fig. 4(b). Membership function of $PM_{2,5}$

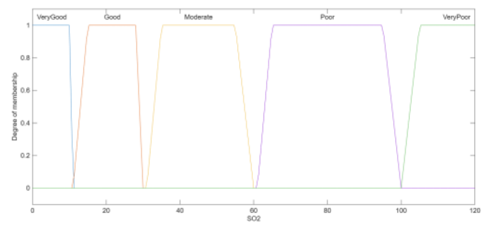

Fig. 4(c). Membership function of SO_2

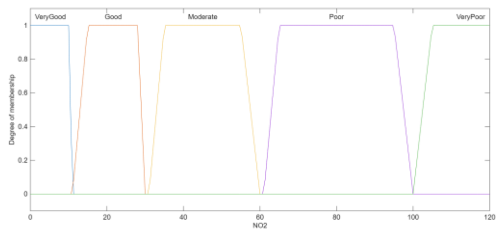

Fig. 4(d). Membership function of NO_2

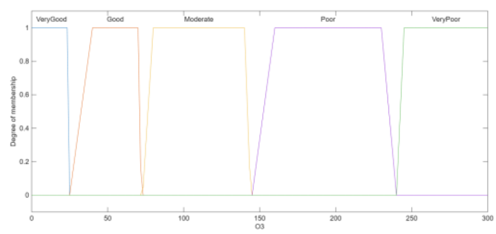

Fig. 4(e). Membership function of O3

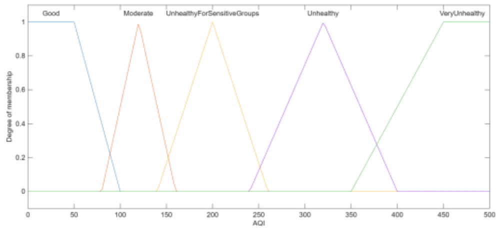

Fig. 5. Membership function of output AQI

Table 2 presents the trapezoidal membership function parameters for each input variable (PM_{10}, $PM_{2.5}$, O_3, NO_2, SO_2), while Table 3 shows the corresponding parameters for the output variable (AQI). These parameters define the fuzzy sets used in the FIS for air quality evaluation.

TABLE 2 PARAMETERS FOR MEMBERSHIP FUNCTION OF THE INPUTS

AQI Category	PM_{10} [a b c d]	$PM_{2.5}$ [a b c d]	O_3 [a b c d]	NO_2 [a b c d]	SO_2 [a b c d]
Very Good	[0 0 9 10]	[0 0 5 6]	[0 0 24 25]	[0 0 10 11]	[0 0 10 11]
Good	[9 12 24 27]	[5 7 13 15]	[25 40 70 72]	[11 15 28 30]	[11 15 28 30]
Moderate	[27 30 51 54]	[15 18 28 30]	[73 80 140 144]	[31 35 55 60]	[31 35 55 60]
Poor	[54 60 85 90]	[30 35 45 50]	[145 160 230 240]	[61 65 95 100]	[61 65 95 100]
Very Poor	[90 100 150 150]	[50 55 100 100]	[240 245 300 300]	[100 105 120 120]	[100 105 120 120]

TABLE 3 PARAMETERS FOR MEMBERSHIP FUNCTION OF THE OUTPUT

AQI Category	AQI [a b c d]
Very Good	[0 0 50 100]
Good	[50 100 100 150]
Moderate	[150 150 200 250]
Poor	[250 250 300 350]
Very Poor	[350 400 500 500]

III) Fuzzy Rules

The rules determine how the membership functions of the inputs and output are used in the fuzzy inference process. These rules are linguistic in nature and are expressed as "IF–THEN" statements. The proposed fuzzy model is based on the Mamdani fuzzy inference structure, as described in Equation 2 [4].

$$R_i\text{: IF } X_1 \text{ is } L_1 \wedge X_2 \text{ is } L_2 \wedge X_3, \ldots \text{is } L_{M-1} \wedge X_M \text{ is } L^i_M \text{ THEN } \mu^i_R \to Y \quad (2)$$

Where i: 1,…,*n*
L` ∈ $\{L_{j,k}\}$ *j*:1,…,*m*; *k*:1,…,*n*; *n*: the number of linguistic labels defined for the *j* input variables; $R_i$ is the *i*-th rule in the set of fuzzy rules: $X_M$ is L`$_M$ states that the fuzzy input variable X_M has a certain linguistic value in L`; $\mu^i_R \to Y$ implies that the degree of membership μ in the rules dictates the consequent fuzzy set Y.

Figure 6 shows the table with rules in that is set up in the rule editor in MATLAB software. There are generated 16 rules used to evaluate the AQI by using Mamdani IF-THEN rules to determine whether it is good, moderate, unhealthy for the sensitive groups, unhealthy and very unhealthy. The rules below show an example of IF-THEN rules of AQI implemented in the MATLAB software.

	Rule	Weight	Name
1	If PM10 is VeryGood and PM25 is VeryGood and O3 is VeryGood and NO2 is Ve	1	rule1
2	If PM10 is Good and PM25 is Good and O3 is Good and NO2 is Good and SO2	1	rule2
3	If PM25 is Good and NO2 is Good then AQI is Moderate	1	rule3
4	If PM25 is Moderate and NO2 is Moderate then AQI is UnhealthyForSensitiveGr	1	rule4
5	If O3 is Moderate then AQI is UnhealthyForSensitiveGroups	1	rule5
6	If PM10 is Moderate and SO2 is Moderate then AQI is UnhealthyForSensitiveGr	1	rule6
7	If PM25 is Poor then AQI is Unhealthy	1	rule7
8	If PM25 is VeryPoor then AQI is VeryUnhealthy	1	rule8
9	If PM10 is Poor and NO2 is Moderate then AQI is Unhealthy	1	rule9
10	If PM10 is VeryPoor then AQI is VeryUnhealthy	1	rule10
11	If NO2 is Poor then AQI is Unhealthy	1	rule11
12	If NO2 is VeryPoor then AQI is VeryUnhealthy	1	rule12
13	If SO2 is Poor then AQI is Unhealthy	1	rule13
14	If SO2 is VeryPoor then AQI is VeryUnhealthy	1	rule14
15	If O3 is Poor then AQI is Unhealthy	1	rule15
16	If O3 is VeryPoor then AQI is VeryUnhealthy	1	rule16

Fig. 6. The rule base coded using MATLAB software

IV) Defuzzification

Defuzzification is the process of converting fuzzy values into crisp outputs. In this study, the centroid method is applied, which is one of the most commonly used techniques for defuzzification. Using this approach, the fuzzy number is geometrically determined to produce a single crisp value [4].

After defining the rules, the data has been inserted in the Rule Viewer and the result is generated as shown in the right-end column of Figure 7. The figure visualizes how input variables are processed through a Mamdani-type Fuzzy Inference System to produce an output value for the AQI.

On the left side, are displayed the input variables PM10, PM2.5, O_3, NO_2, and SO_2. Each input has a numerical value at the top for every input value (e.g., PM_{10} = 75, $PM_{2.5}$ = 50, etc.) and a set of horizontal bars representing their membership in different fuzzy sets (such as low, moderate, or high). The coloured regions indicate the degree to which each input belongs to a particular fuzzy category.

Each row corresponds to a fuzzy rule, and the system includes 16 rules in total. These rules combine the input conditions using fuzzy logic to determine their contribution to the output.

On the right side, the output variable AQI is shown. The triangular shapes represent the output membership functions, and the highlighted areas indicate the aggregated result after applying all active rules. The final crisp AQI value (e.g., AQI = 320) is obtained through a defuzzification process.

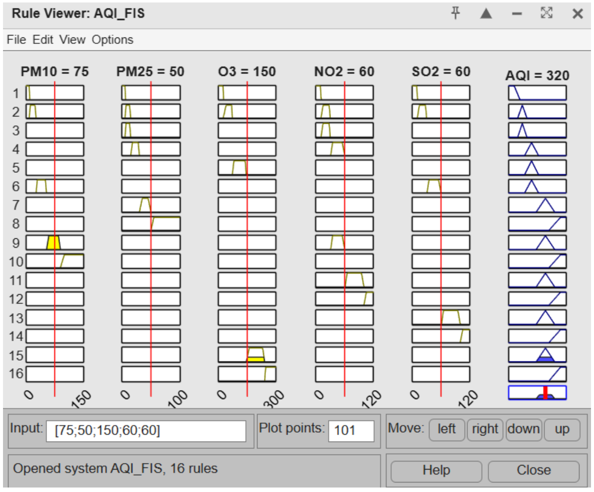

Fig. 7. Rule Viewer (Rules 1-16)

Figure 8 presents a 3D-surface plot illustrating the relationship between particulate matter concentrations and the proposed from FIS AQI. The two horizontal axes represent input air pollutants - PM_{10} and $PM_{2.5}$, while the vertical axis represents the output variable - AQI. The surface shows how variations in particulate matter levels influence the predicted air quality. The colour - from dark blue to yellow - indicates increasing AQI values. Lower AQI values are shown in darker blue regions, while higher values transition through green and orange to yellow, representing poorer air quality conditions. The surface is mostly flat at lower pollution levels, suggesting relatively stable and lower AQI values.

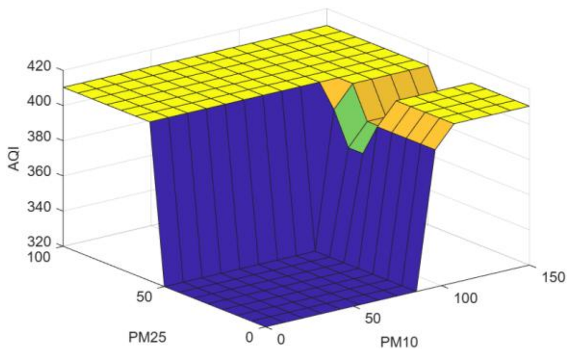

Fig. 8. Surface view of the particulate matter in FIS

III. Findings and Discussion

The proposed model consists of several sequential steps for predicting and evaluating the AQI using fuzzy logic. First, hourly air quality and environmental data are collected from monitoring station, such as those located in Berlin. The input parameters include major air pollutants such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, and O_3, while the output variable is the AQI.

Next, appropriate ranges are defined for each pollutant concentration and AQI level. The pollutant concentrations are categorized into linguistic terms such as Very Good, Good, Moderate, Poor, and Very Poor. Similarly, AQI values are classified into categories including Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, and Very Unhealthy.

In the fuzzification stage, the crisp numerical pollutant values are converted into fuzzy linguistic variables. Membership functions, typically triangular or trapezoidal in shape, are defined to represent the degree of belonging of each input value to a specific linguistic category.

After fuzzification, a rule base is developed using expert knowledge and environmental standards. These IF–THEN rules establish relationships between pollutant levels and the corresponding AQI category.

The fuzzy inference process is then carried out using a FIS. Commonly used methods include the Mamdani Fuzzy Inference System, which is interpretable and rule-based, and the Sugeno Fuzzy Model, which is more suitable for optimization and computational efficiency. In this study, the Mamdani Fuzzy Inference System is adopted because of its simplicity and interpretability in AQI prediction.

Following inference, defuzzification is performed to convert the fuzzy output into a single crisp AQI value. Several methods can be applied, including the centroid method and the mean of maxima method. In this work, the centroid method is used due to its wide acceptance and effectiveness.

Finally, the output AQI values obtained from the fuzzy model are evaluated by comparing the predicted AQI values with the actual AQI measurements. This comparison helps assess the accuracy and overall performance of the proposed fuzzy logic model.

Table 4 presents a small set of real air quality data along with a comparison between the FIS-predicted AQI and the actual measured AQI. The air quality data used in this study are obtained from a monitoring station located in Berlin (Frankfurter Allee). The dataset includes hourly measurements of the following pollutants: PM_{10}, $PM_{2.5}$, NO_2, and O_3. However, it is important to note that SO_2 (sulfur dioxide) measurements are not available from this station. Despite this limitation, the developed fuzzy inference system (FIS) includes SO_2 as one of its input variables. To address this issue, a constant value of zero

(SO_2 = 0) was used as a placeholder during the AQI prediction process.

TABLE 4 RESULT OF COMPARISON BETWEEN ACTUAL AQI AND FIS OUTPUT

Date Time	PM_{10}	$PM_{2,5}$	NO_2	O_3	SO_2	FIS AQI	Actual AQI
01.03.2026 00:00	22	10	20	56	0	68.66	54.267
01.03.2026 01:00	16	7	14	66	0	74.98	86.933
01.03.2026 02:00	20	6	10	70	0	88.54	100
01.03.2026 03:00	14	6	17	62	0	61.45	73.867
01.03.2026 04:00	12	7	13	62	0	65.33	73.867
01.03.2026 05:00	13	8	10	65	0	74.76	83.667
01.03.2026 06:00	11	6	10	69	0	105.45	96.733
01.03.2026 07:00	9	6	15	64	0	75.16	80.4
01.03.2026 08:00	13	6	16	65	0	76.12	83.667
01.03.2026 09:00	25	8	17	66	0	81.99	86.933
01.03.2026 10:00	23	9	15	63	0	82.76	83.667
01.03.2026 11:00	21	10	16	61	0	81.54	84.863
01.03.2026 12:00	22	9	15	64	0	80.76	84.377

The results presented in this study are based on one week of hourly measurements. The developed fuzzy inference system is based on a relatively small rule base consisting of 16 rules. While this limited number of rules is sufficient to capture the general behavior of air quality and provides reasonably accurate AQI predictions, it does not fully represent all possible combinations of pollutant conditions. As a result, some deviations between the FIS-predicted AQI and the actual AQI were observed.

Table 5 shows the comparison between linguistic values of the FIS output and the actual AQI values from Table 4. Most of the predicted AQI values were classified as *Moderate*, which matched the actual AQI classifications. The results show that the system performed well in predicting the correct air quality category. Out of the thirteen observations, twelve were correctly classified by the FIS. Only one value showed a mismatch, where the FIS predicted an AQI of 105.45 and classified it *as Unhealthy for Sensitive Groups*, while the actual AQI value was 96.733 and belonged to the *Moderate* category. This difference occurred because the predicted value slightly exceeded the threshold value of 100, which separates the two linguistic categories. Overall, the results indicate that the FIS provides reliable AQI classification and effectively handles gradual transitions between air quality categories through fuzzy logic reasoning.

TABLE 5 RESULT OF COMPARISON BETWEEN LINGUISTIC VALUE OF ACTUAL AQI AND FIS OUTPUT

FIS AQI	Linguistic Value	Actual AQI	Linguistic Value
68.66	Moderate	54.267	Moderate
74.98	Moderate	86.933	Moderate
88.54	Moderate	100	Moderate
61.45	Moderate	73.867	Moderate
65.33	Moderate	73.867	Moderate
74.76	Moderate	83.667	Moderate
105.45	Unhealthy for Sensitive Groups	96.733	Moderate
75.16	Moderate	80.4	Moderate
76.12	Moderate	83.667	Moderate
81.99	Moderate	86.933	Moderate
82.76	Moderate	83.667	Moderate
81.54	Moderate	84.863	Moderate
80.76	Moderate	84.377	Moderate

The comparison results indicate the overall performance of the model. From the total data based on one week and collected within 168 hours, there are 149 TRUE statements and 18 FALSE statements. The level of accuracy rate is calculated as follows:

$$\text{Accuracy Rate} = \frac{149}{168} \times 100 = 88{,}69\%$$

However, the model performance can be further improved by incorporating a larger and more diverse dataset. To improve the accuracy and robustness of the model, the rule base can be expanded by adding more fuzzy rules. A larger and more detailed rule set would allow the system to better handle different pollutant interactions and provide smoother and more precise AQI predictions.

The results of comparison between the actual AQI values and the FIS-predicted AQI demonstrates that the fuzzy inference system provides a good approximation of real air quality conditions. Furthermore, the FIS output follows the same trend as the actual AQI, although slight overestimations and underestimations were observed. These can be reduced by incorporating more extensive datasets and refining the fuzzy rule base.

IV. CONCLUSION

The main objective of this study was to accurately predict the Air Quality Index (AQI) using a proposed Fuzzy Inference System (FIS) model. A Mamdani-based

FIS was developed to evaluate AQI by considering five major input pollutants: PM_{10}, $PM2_{.5}$, NO_2, O_3 and SO_2. The evaluation process follows four key steps: fuzzification, fuzzy inference, application of fuzzy rules, and defuzzification. The model demonstrated a good accuracy rate, indicating that the proposed Mamdani FIS effectively predicts AQI and provides a reliable tool for assessing air quality; however, the model can be extended and improved by expanding the fuzzy rule base and incorporating more extensive and diverse datasets.

ACKNOWLEDGEMENTS

This work was supported by the NSP “Security and defence” program, which has received funding from the Ministry of Education and Science of the Republic of Bulgaria under the grant agreement no. Д01-74/19.05.2022.

REFERENCES

[1] Umweltbundesamt, “Der Liftqualitätsindex - LQI“.[Online].Available:https://www.umweltbundesamt.de/themen/luft/luftqualitaet/der-luftqualitaetsindex-lqi#der-luftqualittsindex-lqi-des-umweltbundesamtes [Accessed: April. 01, 2026].

[2] Berliner Luftgütemessnetz Stationsdaten: 174 Frankfurter Alleee. [Online].Available:https://luftdaten.berlin.de/station/mc174 [Accessed: April. 01, 2026].

[3] Science Direct, “Fuzzy Inference System”.[Online].Available:https://www.sciencedirect.com/topics/engineering/fuzzy-inference-system [Accessed: April. 01, 2026].

[4] N.Shafii, N. Ramle, R.Alias,D.Nasir, “Application of Fuzzy Inference System in the Prediction of Air Quality Index”, September 2021. ”.[Online].Available: https://www.researchgate.net/publication/354871675_Application_of_Fuzzy_Inference_System_in_the_Prediction_of_Air_Quality_Index [Accessed: April. 01, 2026].

[5] Codecrucks, “What is fuzzy membership function - a complete guide”, 2021.[Online].Available: https://codecrucks.com/what-is-fuzzy-membership-function-complete-guide/ [Accessed: Mai. 05, 2026].

[6] S.Himanshu,Y.A.Lone, “Deep Neuro-Fuzzy Systems with Python”, Apress, December 2019

[7] R.Saatchi, “Fuzzy Logic Concepts, Developments and Imlementation”, October 2024.[Online].Available: https://www.mdpi.com/2078-2489/15/10/656 [Accessed: April. 01, 2026].

[8] World Health Organisation. [Online]. Available: https://www.who.int/tools/air-quality-standards [Accessed: April.08,2026]

[9] Z.Zulkiflee, A. Idris, “Fuzzy Inference System Model for Air Quality Index Prediction” 2024.[Online].Available: https://science.utm.my/procscimath/wp-content/uploads/sites/605/2024/09/133-143-ZULFAZLEEN-NATASHA-BINTI-ZULKIFLEE-A20SC0435.pdf [Accessed: April. 08, 2026].

[10] H. Liu., Q. Li, D. Yu., & Y. Gu.: Air quality index and air pollutant concentration prediction based on machine learning algorithms, 2019, Applied Sciences (Switzerland).[Online].Available: https://doi.org/10.3390/app9194069 [Accessed: April. 08, 2026].

[11] R. Kumaravel, V. Vallinayagam.: A Fuzzy Inference System for air quality in using Matlab, Chennai, India. In J. Environ. Res. Develop. Journal of Environmental Research And Development (Vol. 7, Issue 1).

[12] Matlab Hilfe Center, “Mamdani and Sugeno Fuzzy Inference Logic”.[Online].Available:https://de.mathworks.com/help/fuzzy/types-of-fuzzy-inference-systems.html [Accessed: April. 08, 2026].

[13] H.Herpratiwi, M.Maftuh, W.Firdaus, A.Tohir, M.Daulay, R.Rahim, “Implementation and Analysis of Fuzzy Mamdani Logic Algorithm from Digital Platform and Electronic Resource”, August 2022.[Online].Available: https://www.researchgate.net/publication/363144501_Implementation_and_Analysis_of_Fuzzy_Mamdani_Logic_Algorithm_from_Digital_Platform_and_Electronic_Resource [Accessed: April. 08, 2026].

[14] K.Pujaru, S.Adak, T.K.Kar, S.Patra, S.Jana, “A Mamdani fuzzy inference system with trapezoidal membership functions for investigation fishery production”, May 2024.[Online].Available: https://www.sciencedirect.com/science/article/pii/S2772662224000857 [Accessed: April. 08, 2026].

[15] D.Dunea, A.A.Pohoata, E.Lungru, “Fuzzy inference system for estimation of air quality index”.[Online].Available: https://rj.romai.ro/arhiva/2011/2/Dunea-et-al.pdf [Accessed: April. 08, 2026].

[16] IQAir, “Air quality in Berlin”.[Online].Available: https://www.iqair.com/germany/berlin/berlin [Accessed: April. 05, 2026].

[17] Matlab Hilfe-Center, “Fuzzy Inference System Modeling”.[Online].Available: https://de.mathworks.com/help/fuzzy/fuzzy-inference-system-modeling.html [Accessed: April. 05, 2026].

[18] M.Saleem, N.Shingari, M.Farooq, B.Mago, M.Khan, “Real-Time Air Quality Monitoring Model using Fuzzy Inference System”, 2024.[Online].Available: https://thesai.org/Downloads/Volume15No6/Paper_84-Real_Time_Air_Quality_Monitoring_Model.pdf [Accessed: April. 05, 2026].