Real-Time Air Quality Monitoring Model using Fuzzy Inference System

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***Abstract*—Air pollution, which is both environmental and social, is a serious issue that affects people's health as well as ecosystems and the environment. Air pollution currently poses a number of health problems to the ecosystem. The most important factor that has a direct impact on disease occurrence and decreases people's quality of life is city and metropolitan air quality. It is critical to establish real-time air quality monitoring in order to make timely decisions based on measurements and evaluations of environmental factors. Monitoring systems are influential in multiple smart city initiatives for keeping an eye on air quality and reducing pollutant concentrations in metropolitan areas. The Internet of Things (IoT) is becoming increasingly important in a variety of sectors, including air quality monitoring. In this research work, a real-time air quality monitoring model employing fuzzy inference is proposed for monitoring air pollution using multiple parameters such as Sulphur Dioxide (SO2), Nitrogen Dioxide (NO2), Carbon Monoxide (CO), Ozone (O3) and Suspended Particulates (PM10). This proposed research presents a novel technique for improving air quality monitoring. This proposed fuzzy inference system also provides better results in terms of monitoring air quality in a more efficient and effective way.**

***Keywords*—IoT; fuzzy inference system; smart city; air quality monitoring**

I. Introduction

Beginning the viewpoint of conventional urban policy, there are numerous debates and recommendations on smart cities (cities that have implemented smart services). Technology focused Smart City (SC) initiatives have been criticized for obliterating the various layers of variables that surround SCs. Since smart cities require technological fundamentals and the dynamic fundamentals nearby, governments that fail to recognize multiple factors when implementing smart policies will not offer eminence facilities to people effectually (e.g., the policy ecology and urban substructure). Via an analytic hierarchy process research, this research investigates the causes of smart cities besides their goalmouths.

Smart Cities also appear some obstacles in their operation, but additional Smart City research programs are being funded and implemented regularly. Furthermore, cities worldwide are adopting Smart City structures to boost facilities or residents' superiority of life. We review current Smart City concepts in the literature, assess existing tools and systems, review the different areas of implementations where these techniques and methodologies are being used (e.g., health and education), display cities that have incorporated the Smart City model into their everyday operations, that include a review of the academic literature [1].

The terms IoT and "Smart City (SC)" are often utilized to describe how to deal with the complexities of modern city operations. The key challenges that city operators face are population concentration, resource scarcity, and environmental issues, making ordinary service provisioning less effective. Data in particular domains will be provided by an IoT sensor in the city environment, while control functions will be conducted in the real world by an IoT actuator. Smart IoT systems that operate on IoT or cross-sector elements are interconnected systems which enable useful data and knowledge exchange [2, 3].

There are some factors to remember when planning a smart city. These factors are: social, technological, economic, political and environmental. Finally, the environmental issues that impact smart cities, include water management, food security, infrastructure development, ecosystem services, source reduction, severe weather, Air Pollution (AP), noise, and recycling. Loss of biodiversity, heat stress, sanitation, semi-transportation, land use patterns, sea-level rise, construction use, and transportation motorization are only a few of the issues that need to be addressed. The topic of air pollution is explored in depth here.

With the ongoing growth and increase in population inside metropolitan areas, a number of environmental concerns such as deforestation, uncontrolled hazardous chemicals, solid waste management, pollution, and others have gotten a lot more attention than ever before. Also, the rapid growth in manufacturing and transportation has resulted in increased pollution being a severe issue, which both governments and citizens have given increased attention. According to the World Health Organization (WHO) research, long-term contact with outdoor and indoor particulate matter, an air pollution type, has resulted in around seven million deaths globally, ranking fifth among all hazards [4, 5].

The pollution is known as chemicals under natural settings introducing and giving rise to the damage. Pollution may be caused by chemical compounds or energy, like noise, heat, or light. Pollutants are chemicals or fuels that are either foreign or

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naturally occurring and cause pollution. Air pollution is described as contaminants in the atmosphere, harmful to human and living beings' health, or affecting materials or climate. Ammonia, Carbon Dioxide (CO_2), SO_2, Particulate Matter (PM), methane, and hydrogen cyanide are all forms of air contaminants, particulates (both inorganic), and organic macromolecules. AP may harm humans by causing infections, asthma attacks, and even mortality, as well as animals, food crops, and natural and built ecosystems. All Green-House Gases (GHGs) and geological cycles can pollute the air.

When carbon rise at a certain level in the air, it can be dangerous to us. Individuals are forced to live in places with poor air quality that includes smog, particulate pollution and toxic chemicals hazardous to their health. A high concentration of particular air pollutants can cause:

- Irritation of the nostrils, eyes and throat.
- Breathing issues, which normally include wheezing, coughing, chest pain, and respiratory problems such as asthma and shortness of breath.
- Escalation of chronic respiratory and cardiac illnesses, for instance, asthma.
- Increase in the attack risk of cardiac infarction.

Prolonged exposure to AP can develop into cancer and be harmful to the immune, endocrine, nervous and respiratory systems. A serious tone underlies it because death is a possibility in extreme cases. All living beings of life are impacted by air pollution, in which some people are more sensitive to the typical air pollutants like "particulates and ground-level ozone" than others. Pollution, both land- and airborne (pollutants that are particulates in the air), affects many, with children, the elderly, people who engage in outdoor sports, and people with any cardiac or lung disorders being the most sensitive groups to pollution.

An Air Quality Monitoring (AQM) involves the determination of current air pollution levels about "ambient air quality standards"- that are meant to reduce the levels of pollution and has the target of making clean air. Monitoring helps to prevent emergency cases by warning people and forcing them to take action. It monitors "SO_2, NO_2, PM10, PM2.5, ozone, arsenic.

Machine learning techniques, integrated within a real-time air quality monitoring model, can enhance predictive capabilities by leveraging fuzzy inference systems to analyze complex environmental data in real time, facilitating proactive measures for pollution control and public health protection [28-32].

Fuzzy Logic (FL) is employed to map human experts' experiences into mathematical languages which govern in areas uncertain. Decision-making with FL can be maximized. The risk of air pollutants can more or less be ranked by FL through a number between 0 and 1. The assignment can be completed by using FL calculations to define each attribute to the set. A fuzzy management system employs analysis of analogue signal values from logical variables that assume either constant values which lay between 0 and 1 or classical/digital logic which operates on discrete values (1 or 0) instead [33-37].

Machine control normally uses FL in computer control. The word "fuzzy" means that in this controversy, the statements will dwell on partial untruths rather than wholly true or untrue opinions. In other cases, there are alternative methods that can perform well as FL like evolutionary algorithms and neural networks, but still, FL has the privilege of "translating" the solution in a throw that the human operator should be able to understand which will add an experience ingredient that could be utilized in the controller design. Now the tasks are humanized, and it is more probable to automatize human activities [6].

Applying fuzzy logic to air quality monitoring can help in making the results more accurate and faster. Fuzzy logic capability of representing data between 0 and 1 helps in improving the analysis of the general data and hence pollution detection. This approach can help in improving the predictions enabling environmental checks, human health, and city designs. Thus, the use of fuzzy logic yields a positive development in improving air quality monitoring systems for enhanced environmental performance.

II. Literature Review

Researchers have been heavily involved with environmental monitoring, detecting pollutants, and figuring out the sources of pollution using sensor networks. As shown by the other researchers [7, 8], the air pollutants which were most dangerous to human health and were discharged into the air when fossil fuels, gasoline, petrol, and diesel were burnt were nitrogen dioxide, hydrocarbon, and particulate matter. The transportation sector, power generation plants, and manufacturing were the primary sources of these contaminants in Erbil. The use of IoT platforms in several fields, like agriculture, nature tracking, human tracking, and "Air Quality Monitoring (AQM)," has increased in recent years.

In study [9, 10], another important factor influencing emission dispersion calculation was the source of pollution. The point, line, field, and volume sources were the most common air pollutant sources. There were two types of sources: stationary and mobile. Stationary sources include flue gas piles, while mobile sources include vehicles. Air quality monitoring has historically relied on network stations and continuous pollution levels at the local and regional levels. The predominant emission sources were used to classify stations (traffic, industrial and background stations). In comparison to in-field observations, air quality modeling was being used for estimating pollution, especially in areas with no measurement stations. Sensor networks, energy consumption reduction, and data transfer to repositories where this knowledge was analyzed have occupied a large portion of research and literature reviews.

Depending on the service area, the low-cost sensors embedded into the network links that make up the network produce better or worse results. One of the regions where low-cost sensors' performance was being tested was air quality sensors [11]. Sensors for "NO_2, NO, tropospheric O_3, and particle matter (PM2.5, PM5)," etc., were seldom calibrated by the manufacturer. If they were, it was rarely under the conditions in which they can provide measurement data. This lack of quality control has influenced regulations' negative perceptions of sensors and the scientific community's cautious use of them. Consequently, there was a strong demand for strategies to test or validate sensor data to monitor air pollution [12, 13, 14].

"Multiple Linear Regression (MLR)" [15, 16] "K-Nearest Neighbors (KNN), Support Vector Regression (SVR)" [17, 18], and "Random Forest (RF)" [19] have all seen an increase in interest in comparing and evaluating various calibration algorithms in recent years. Many of these studies utilized nodes to deploy a sensor array. This was because air pollutants were often found to have direct or inverse relationships with other pollutants, such as "ozone being negatively correlated with nitrogen oxide due to titration," or with meteorological conditions like temperature and relative humidity.

Air quality fields that take into account of local variations such as emissions and meteorology were one instrument of the CTMs (Chemical Transport Models) [20, 21, 22]. The Community Multiscale Air Quality (CMAQ) was a model that was state-of-the-art Climate Transmission Model (CTM) to track the motion of air pollutants due to anthropogenic pollution. "CMAQ" not only captures the spatial and temporal variations of the given area but also it might be error prone because of the flaws in meteorological, including the failures in emission-blaming characterization [23]. This study seeks to employ the DF method to develop spatiotemporal concentration maps for PM2.5 mass, five PM species, and three gas concentrations across North Carolina. These maps will be used for a health study focusing on coronary heart disease patients affiliated with the University of North Carolina Chapel Hill. The data fusion system combines information from atmospheric sensors with "CMAQ" to generate ground-level air pollution intensity fields for more accurate exposure estimates on spatial resolution of 12 km. Different techniques were used to provide data withholding and evaluate the stability of the data fusion and it was examined. The effect of total PM2.5 mass concentration was studied for four methods namely: "unadjusted CMAQ pollute Along with examining the effectiveness of various PM2.5 exposure methods, the approaches were being contrasted. The CMAQ and data fusion results were also compared with respect to the exposure fields of five PM entities and three gases.

In study [24], the authors suggested a fresh approach of building an AQM system based on fog computing and IoT" and described an embedded system where air quality data is collected over a time-frame and transferred to fog nodes for processing. Processing will be carried out to the simple information such as regular measurements, and further analyze it in the cloud under long-term storage. The cloud might be a good place to perform global analytics on data acquired from shared equipment over a long period. The infrastructure and model were developed using microprocessors and IoT-cloud platforms. Experimental findings show that this approach was capable of sensing air quality, and long-term air monitoring will help better understand air pollution and find a way to reduce it. This system has no restrictions on where it may be installed. The IoT-cloud was used to estimate air quality data as well as create data visualizations for the end-user.

In study [25], research project on the growth of the "IoT-based Air Pollution Monitoring System (APMS)" was undertaken and it involved an Arduino processor, sensor nodes to detect the existence of hazardous gases in the air, a mobile unit, a temporary memory buffer, and an internet connected web server. At a time, it locates data from many places and organizes the information at a particular instant of the day. A GPS module was connected to the system to precisely depict pollution sources in a given region. The collected data was sent to a computer regularly via a GPRS connection and subsequently displayed on a specific website. This system monitors air quality and will give notification when it is under an agreed limit, e.g., when there's a large amount of poisonous gases in the air, like "CO2, smoke, benzene, as well as NH3." It will display the feature in ppm on LCD and the website so that authorities can know and tackle air pollution in various regions.

The research in [26] introduced a novel evaluation model that incorporates a "FIS and an Analytic Hierarchy Process (AHP)" to create a new "Air Quality Index (AQI)." The toxicological values of environmental parameters ("PM2.5, PM10, O3, CO, NO2, and SO2") were assessed. The primary aim was to give effective evaluation through a "Reasoning Process (RP)" driven by priority weighting. The FIS processes air quality parameters based on their permissible limits in the first phase. Then, using RP, multiple air quality scenarios were modelled. As a result of combining such evaluations, a global score of the air quality situation was generated. FIS analyzes all the contaminants using the same classification system, which could cause complexity when air pollutants can lead to other different health issues. Eventually, in the last step, the system must include weightings derived from the importance of each significant parameter leading to air quality level or Air Quality Index (AQI). Lastly, based on the "Mexico City atmospheric monitoring system" data, the model analyses five score stages: in accordance with "severe, bad, good, regular and dangerous" when we put the weighted measures based on the classification in the pollution air, the results of the experiments discloses that the proposed AQI have better evaluations than the other classical AQI.

The impact of poor indoor air conditions on overall human quality of life is 10 times more damaging than outdoor air pollution where we are dealing with chemical hazards and other toxic substances. The "Environment Indoor Air Quality (EIAQ)" index plays a critical role in establishing the EIAQ that was good for human health by integrating the indoor AQI and "Thermal Comfort (TC) index." [27] introduced an "EIAQ monitoring" and control system that uses "Fuzzy Logic Controller (FLC)" to recognize, categorize, and calculate the EIAQ index value, which was divided into four categories: "'epic , 'ok', 'horrible', and 'worst'" Additionally, there was a selecting of contaminants that were grouped together based on their similar internal characteristics as well as the impact on people's health and environment. This approach uses "rule-based fuzzy logic" to process data obtained from a variety of sensors. The FIS' primary goal was to create an EIAQ index based on fuzzy theory. The EAQI index values served as reference points for the control system, which included fans, inlet-outlet exhaust, a buzzer, and lead components. This system was implemented to enhance indoor air quality and to provide updates on the status of air TC pollutants. Thus, by and large, these models proved to be of great value in the area of evaluation, classification, of risk analysis, making suggestions, and undertaking actions to raise the well-being level of people.

III. Proposed Air Quality Monitoring Model

Air quality is an integral part of our lives. Smart cities are the main assets that provide their residents with a better quality of life with the provision of a safe and healthy atmosphere. In a smart city, environmental factors must be monitored to detect and mitigate pollution sources. In this research, a model is proposed to predict pollution nodes throughout the region to track pollution and meteorological parameters. By seeing breakdown, the community will take corrective action and enhance its environmental health. People may be warned of a disastrous event by implementing disaster warning devices, e.g., flooding and rainfall forecasting solutions. A holistic perspective can be obtained, allowing authorities to take data-driven infrastructure or policy planning decisions.

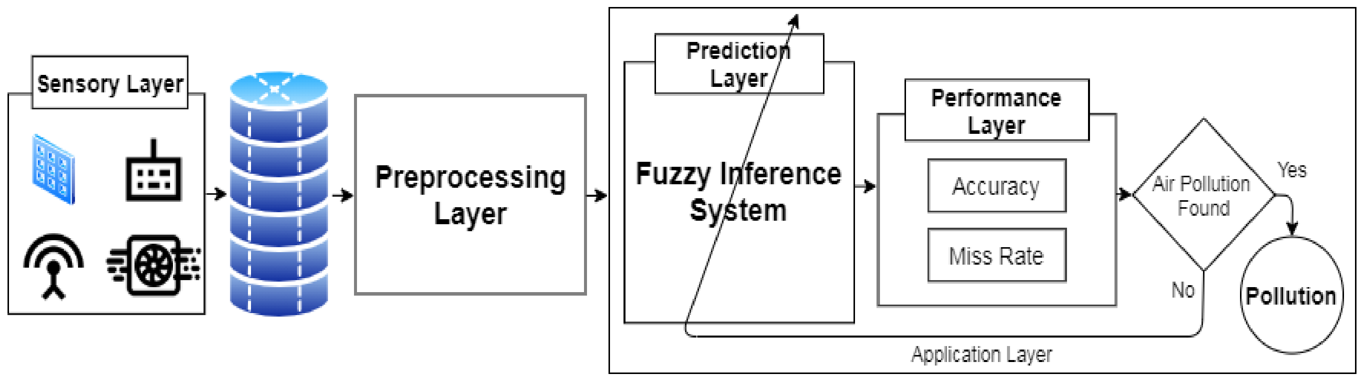


Fig. 1. Proposed model for air quality monitoring.

The following Fig. 1 depicts the waste disposal model. The layer with input values is called the input layer. The proposed methodology depends on three layers: “This layer incorporates Sensory Layer, Preprocessing layer, and Application layer.” The Sensory layer deals with parameters input like Sulfur Dioxide (SO2), (NO2), CO, Ozone (O3) and Suspended Particulates (PM10), which get the values from parameters and pass these values through The IoT is the source of raw data because communication is wireless transmission. Maybe it is given some values that it misses or not, but the data may be noisy, too. That’s why it’s raw data. The top layer of the next layer is the preprocessing layer.

As you can see in Fig. 2, preprocessing involves the extraction of features through normalization and tokenization. Replacing missing data with moving averages and normalization is a crucial preprocessing step aimed at eliminating noise. The processed output from the preprocessing layer is then fed into the application layer, which is further subdivided into the prediction layer and the performance layer.

In Fig. 3, the prediction layer depicts a fuzzy inference engine. When the input parameter is pertinent, it undergoes fuzzification to translate it into fuzzy crisp inputs. This process starts with collecting clear input data, then transforming it into a fuzzy set using fuzzy linguistic variables, fuzzy semantic terms, and membership functions within the fuzzifier. Afterward, the fuzzy enhancements are analyzed through the fuzzy inference engine. Fuzzy inference involves determining an output based on a given input using fuzzy logic, followed by the transformation of fuzzy set values to a precise set in the defuzzifier. This process is commonly utilized in fuzzy control systems. Ultimately, the crisp output value determines whether pollution is predicted. The output from the prediction layer is accelerated to the performance layer for pollution detection, evaluating accuracy and miss rates. If pollution is detected, a message is displayed; otherwise, the fuzzification is adjusted.

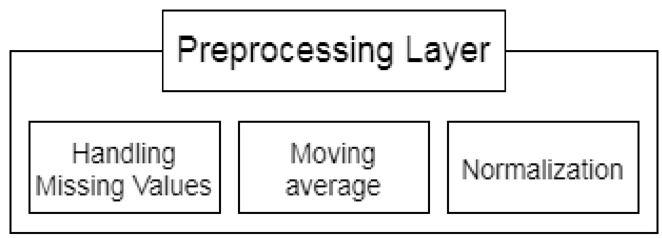


Fig. 2. Framework for preprocessing layer.

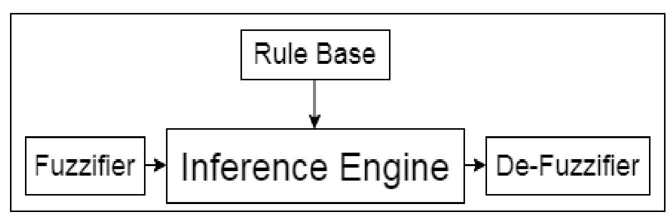
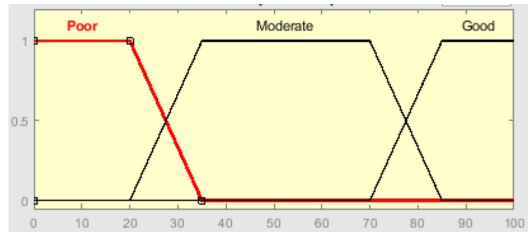
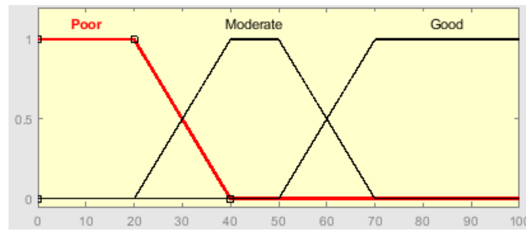
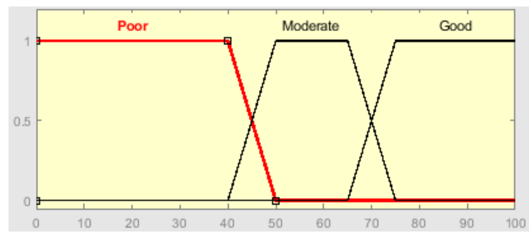
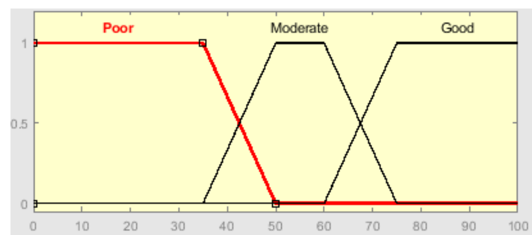
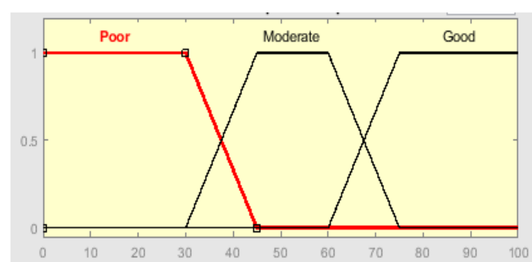
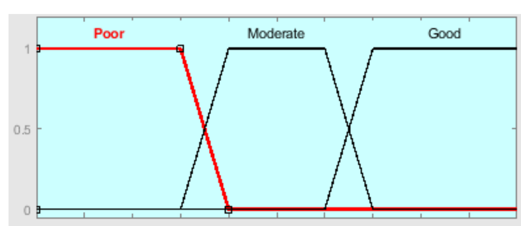


Fig. 3. Fuzzy inference engine.

IV. Membership Functions

A MF gives a statistical overview of input and output variables, showing how input variables are organized to generate membership values ranging from 0 to 1. Table I displays the membership functions of the suggested model's input/output variables for mapping, cluster module, device controller, service controller, and cloud ranking, presented graphically and mathematically.

TABLE I. MEMBERSHIP FUNCTIONS OF AIR QUALITY

Input/Output	Membership Functions	Graphical Representation of MF
Sulphur-Dioxide (SO_2)= $\mu_{SO2}(so2)$	$\mu_{SO2}(so2) = \{\max(\min\left(1, \frac{35 - so2}{15}\right), 0)\}$ $\mu_{SO2}(so2) = \{\max(\min\left(\frac{so2 - 20}{15}, 1, \frac{85 - so2}{15}\right), 0)\}$ $\mu_{SO2}(so2) = \{\max(\min\left(\frac{so2 - 70}{15}, 1\right), 0)\}$	
Nitrogen Dioxide (NO_2)=$\mu_{NO2}(no2)$	$\mu_{NO2}(no2) = \{\max(\min\left(1, \frac{40 - no2}{20}\right), 0)\}$ $\mu_{NO2}(no2) = \{\max(\min\left(\frac{no2 - 20}{20}, 1, \frac{70 - no2}{20}\right), 0)\}$ $\mu_{NO2}(no2) = \{\max(\min\left(\frac{no2 - 50}{20}, 1\right), 0)\}$	
Carbon mono Oxide (CO)=$\mu_{CO}(co)$	$\mu_{CO}(co) = \{\max(\min\left(1, \frac{50 - co}{10}\right), 0)\}$ $\mu_{CO}(co) = \{\max(\min\left(\frac{co - 40}{10}, 1, \frac{75 - co}{10}\right), 0)\}$ $\mu_{CO}(co) = \{\max(\min\left(\frac{co - 65}{10}, 1\right), 0)\}$	
Ozone (O_3) = $\mu_{O3}(o3)$	$\mu_{O3}(o3) = \{\max(\min\left(1, \frac{50 - o3}{15}\right), 0)\}$ $\mu_{O3}(o3) = \{\max(\min\left(\frac{o3 - 35}{15}, 1, \frac{75 - o3}{15}\right), 0)\}$ $\mu_{O3}(o3) = \{\max(\min\left(\frac{o3 - 60}{15}, 1\right), 0)\}$	
Suspended Particulates (PM_{10})=$\mu_{PM10}(pm10)$	$\mu_{PM10}(pm10) = \{\max(\min\left(1, \frac{45 - pm10}{15}\right), 0)\}$ $\mu_{PM10}(pm10) = \{\max(\min\left(\frac{pm10 - 30}{15}, 1, \frac{75 - pm10}{15}\right), 0)\}$ $\mu_{PM10}(pm10) = \{\max(\min\left(\frac{pm10 - 60}{10}, 1\right), 0)\}$	
Air Quality (AQ)=$\mu_{AQ}(aq)$	$\mu_{AQ}(aq) = \{\max(\min\left(1, \frac{40 - aq}{10}\right), 0)\}$ $\mu_{AQ}(aq) = \{\max(\min\left(\frac{aq - 30}{10}, 1, \frac{70 - aq}{10}\right), 0)\}$ $\mu_{AQ}(aq) = \{\max(\min\left(\frac{aq - 60}{10}, 1\right), 0)\}$	

V. Fuzzy Set Operations

The Union and Compliment are the most vital Fuzzy Set Operations to manage the essence of FL. If there are two fuzzy sets, A and B on the universe X, $x \in X$.

Then the FSO can be written as

Intersection (AND) = $\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x))$

Union (OR) = $\mu_{AUB}(x) = \max(\mu_A(x), \mu_B(x))$,

Additive Complement (NOT) = $\mu_A(x) = 1 - \mu_B(x)$

VI. Fuzzy Propositions

A proposition represents a statement that can be categorized as either true or false. A multi-layered architecture has been proposed to assess cloud automation, structured into two levels of layers.

VII. Layer Level 1

Here, Layer 1 contains 5-factor layers' correspondence with AQ. Every layer has its MF represented by variables.

$$\text{AQ} = \text{t: SO2 x NO2 x CO x O3 x PM10} \rightarrow \text{T1} \tag{1}$$

In the realm of fuzzy expert systems, all qualities of input and output variables are mapped from the real range to probability ranges, given that the system operates within a probability range of 0 to 1. The T-norm function of Layer Level 1 can be expressed as:

$$\text{AQ} = \text{t}: [0,1]\text{x} [0,1] \text{ x } [0,1]\text{x} [0,1]\text{x} [0,1] \rightarrow \text{T1} \tag{2}$$

Eq. (1) to Eq. (2) convert the MFs of fuzzy sets of simulation, Air Quality as Layer Level 1 is:

From Eq. (1) to (2)

$$t\big[\mu_{SO2}(so2), \mu_{NO2}(no2), \mu_{CO}(co), \mu_{O3}(o3), \mu_{PM10}(pm10) = \min\big(\mu_{SO2}(so2), \mu_{NO2}(no2), \mu_{CO}(co), \mu_{O3}(o3), \mu_{PM10}(pm10)\big)\big] \tag{3}$$

Specify equation (from 3)

$$\mu_{SO2 \cap NO2 \cap CO \cap O3 \cap PM10}(so2, no2, co, o3, pm10) = t[\mu_{SO2}(so2), \mu_{NO2}(no2), \mu_{CO}(co), \mu_{O3}(o3), \mu_{PM10}(pm10)] \tag{4}$$

Specify from Eq. (4)

$$\mu_{SO2 \cap NO2 \cap CO \cap O3 \cap PM10}(so2, no2, co, o3, pm10) = min[\mu_{SO2}(so2), \mu_{NO2}(no2), \mu_{CO}(co), \mu_{O3}(o3), \mu_{PM10}(pm10)] \tag{5}$$

Eq. (5) represents the minimum of intersection all sets.

Here, Layer 2 is containing five member functions respectively M, CM, DC, SC and CR. Every layer has their MF represent by variables.

$$\text{t: AQ} \rightarrow Lt \tag{6}$$

$$\text{t: } [0,1] \rightarrow Lt \tag{7}$$

$$t[\mu_{AQ}(aq) = \min[(\mu_{AQ}(aq))] \tag{8}$$

$$\mu_{AQ}(aq) = \min(\mu_{AQ}(aq))] \tag{9}$$

Eq. (9) specifies the minimum of intersection all sets.

VIII. Fuzzy Inference Engine

The Fuzzy Inference Engine (FIE) is the process of combining the fuzzy "IF-THEN" rules from the Fuzzy Rule Base (FRB) to map a fuzzy input set to a fuzzy output, following fuzzy logic principles. Key components of Fuzzy Inference include MFs, fuzzy logic operators, and if-then rules. All instructions within the FRB are consolidated into a Single Fuzzy Relation (SFR), positioned under the internal item on input universes of discourse, which is then treated as a single fuzzy "IF-THEN" rule. A suitable operator for combining the rules is a union.

Layer 1 IF-THEN fuzzy represent as:

$$R_{N^n} = A^n \times B^n \times C^n \dots \times N^n$$

$$\mu_{A \cap B \cap C \dots \cap N}(a, b, c \dots, n) = \mu_A(a) \cap \mu_B(r) \cap \mu_C(c) \dots \cap \mu_N(n) \tag{10}$$

Interpreted as SFR defined by

$$R_n = \cup_{n=1}^{n} R_N^n$$

Suppose φ, λ and ψ be any three arbitrary fuzzy sets and are also input and output to the FIE, respectively. To view R_n as a single fuzzy "IF-THEN" rule and using the generalized modus ponens.

$$\mu_{Range\ 1 \cap Range\ 2 \cap Range\ 3 \dots \cap Range\ n}(\varphi) = Sup_{\lambda \in (A,B,C \dots,N)} t[\mu_\lambda(A, B, C \dots, N), \mu_{R_n}(A, B, C \dots, N)] \tag{11}$$

Product Inference Engine format.

$$\mu_\varphi(T) = \max_{0 \le x \le n} \left[\begin{array}{c} sup_{(a,b,c \dots,n) \in U} \left(\mu_{A,B,C \dots,N}(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c} \dots, \boldsymbol{n}) \right) \\ \left(\left(\prod_{k=1}^{n} (\mu_{a_k, b_k, c_k \dots, n_k}(a_k, b_k, c_k \dots, n_k), \mu_\varphi x(T) \right) \right) \end{array} \right] \tag{12}$$

Layer 2 IF-THAN fuzzy represent as:

$$R_{\beta^n} = A^n \times B^n \times C^n \dots, \times N^n$$

$$\mu_{A \cap B \cap C \dots \cap N}(a, b, c \dots, n) = \mu_A(a) \cap \mu_B(b) \cap \mu_C(c) \dots \cap \mu_N(n) \tag{13}$$

Interpreted as SFR for layer 2 is defined by

$$R_n = \bigcup_{n=1}^{n} R_N^n$$

This is layer 2 is interpreted as SFR, defined as R_{α^n}.

IX. Fuzzy IF-Then Rules (Air Quality)

If-then statements are used to construct conditional statements of fuzzy logic. These statements form the basis for building a fuzzy rule base. The following are a few fuzzy inference procedure rules for the mapping.

1) If (SO2) is Poor) and ((NO2) is Poor) and (Carbon mono Oxide (CO) is Poor) and (O3) is Poor) and (Suspended Particulates (PM10) is Poor) then (Air Quality is Poor)

2) If (SO2 is Good) and (NO2 is Poor) and (CO is Poor) and ((O3) is Poor) and (Suspended Particulates (PM10) is Good) then (Air Quality is Good).

3) If (SO2 is Poor) and (NO2 is Moderate) and (CO is Moderate) and ((O3) is Moderate) and (Suspended Particulates (PM10) is Good) then (Air Quality is Moderate).

4) If (SO2) is Good) and ((NO2) is Good) and (Carbon mono Oxide (CO) is Good) and ((O3) is Good) and (Suspended Particulates (PM10) is Good) then (Air Quality is Good).

X. DEFUZZIFIER

The process of defuzzifier derives an outcome in crisp logic by integrating fuzzy sets and evaluating their membership degrees. This makes a fuzzy set to a fresh set. In fuzzy control frameworks, it is expected to be representative. De-Fuzzifiers are available in a wide range of shapes and sizes. A centroid form of a De-Fuzzifier is used in the proposed model. The De-Fuzzifier graphical representation of FIS of mapping, cluster module, device controller, service controller, and cloud ranking is shown in Fig. 4 to Fig. 8.

Fig. 4 illustrates that if Ozone lies between 50-100 and Suspended Particulates between 50-100 then Air Quality is Good (Yellowish). If Ozone lies between 40-50 and Suspended Particulates between 40-50 then Air Quality is Satisfactory (Greenish). If Ozone lies between 0-40 and Suspended Particulates between 0-40 then Air Quality is Bad (Bluish).

Fig. 5 illustrates that if Ozone lies between 50-100 and SO2 Dioxide between 50-100 then Air Quality is Good (Yellowish). If Ozone lies between 40-50 and SO2 between 40-50 then Air Quality is Satisfactory (Greenish). If Ozone lies between 0-40 and SO2 between 0-40 then Air Quality is Bad (Bluish).

Fig. 6 illustrates that if Ozone lies between 70-100 and SO2 between 80-100 then Air Quality is Good (Yellowish). If Ozone lies between 50-70 and SO2 between 30-80 then Air Quality is Satisfactory (Greenish). If Ozone lies between 0-50 and SO2 between 0-30 then Air Quality is Bad (Bluish).

Fig. 7 illustrates that if SO2 lies between 80-100 and Carbon Mono Oxide between 80-100 then Air Quality is Good (Yellowish). If SO2 lies between 70-80 and Carbon Mono Oxide between 70-80 then Air Quality is Satisfactory (Greenish). If SO2 lies between 0-70 and Carbon Mono Oxide between 0-70 then Air Quality is Bad (Bluish).

Fig. 8 illustrates that if Ozone lies between 80-100 and Nitrogen Dioxide between 80-100 then Air Quality is Good (Yellowish). If Ozone lies between 50-80 and Nitrogen Dioxide between 50-80 then Air Quality is Satisfactory (Greenish). If Ozone lies between 0-50 and Nitrogen Dioxide between 0-50 then Air Quality is Bad (Bluish).

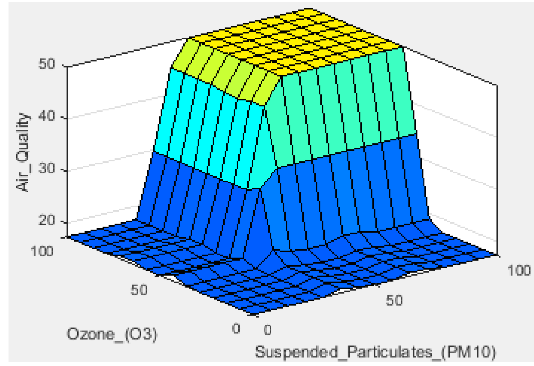


Fig. 4. Rule surface of air quality based on ozone and suspended particulates.

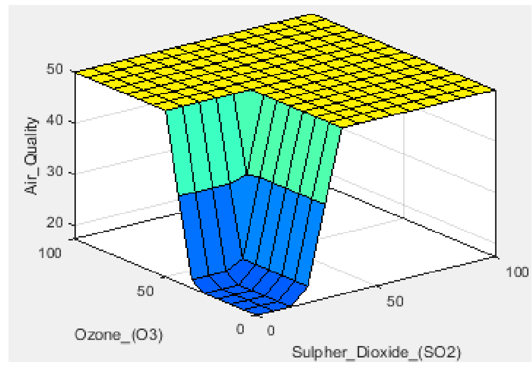


Fig. 5. Rule surface of air quality based on ozone and SO2 (1).

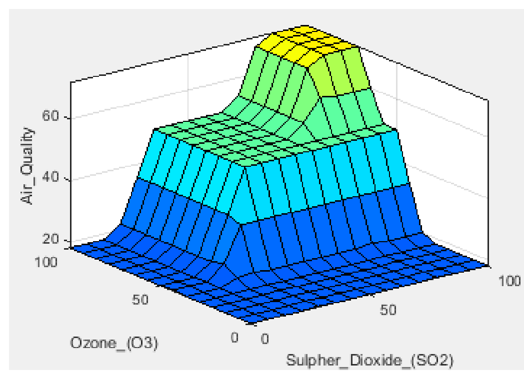


Fig. 6. Rule surface of air quality based on ozone and SO2 (2).

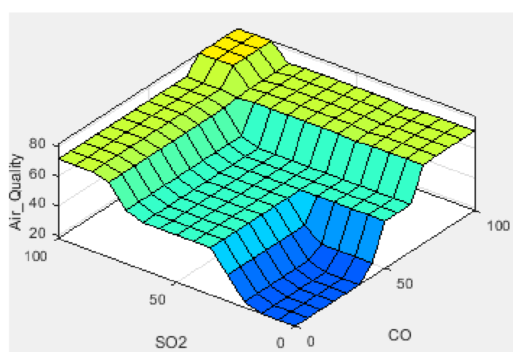


Fig. 7. Rule surface of air quality based on sulphur dioxide and carbon monoxide.

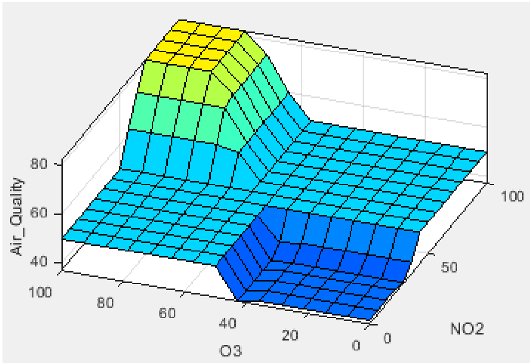


Fig. 8. Rule surface of air quality based on ozone and nitrogen dioxide.

XI. Simulation Results

In fuzzy logic, Boolean logic handles partially true or false values. Boolean values or membership values in fuzzy sets are represented by a number ranging from 0 to 1, where 0 signifies absolute Falseness and 1 represents complete truth. MATLAB is utilized to simulate the Fuzzy system for obtaining simulation results, with the simulated graphs presented in Fig. 9-13. MATLAB finds applications in modeling, simulation, algorithm development, prototyping, and various other domains. To generate the reproduction results, five data sources and one performance factor are employed. The proposed Fuzzy based air quality monitoring model is demonstrated in this article with several outputs such as the proposed system prediction. Based on the lookup rules, a lookup rules diagram is generated using the Fuzzy Logic designer.

Fig. 9 shows that if the values of (SO2) is poor, (NO2) is poor, Carbon Mono Oxide (CO) is poor, (O3) is poor and Suspended Particulates (PM10) is poor then Air Quality is poor.

Fig. 10 shows that if the values of (SO2) is moderate, (NO2) is good, Carbon Mono Oxide (CO) is poor, (O3) is poor and Suspended Particulates (PM10) is poor then Air Quality is poor.

Fig. 11 shows that if the values of (SO2) is moderate, (NO2) is moderate, Carbon Mono Oxide (CO) is moderate, (O3) is moderate and Suspended Particulates (PM10) is moderate then Air Quality is moderate.

Fig. 12 shows that if the values of (SO2) is good, (NO2) is good, Carbon Mono Oxide (CO) is good, (O3) is good and Suspended Particulates (PM10) is good then Air Quality is good.

Fig. 13 shows that if the values of (SO2) is good, (NO2) is poor, Carbon Mono Oxide (CO) is poor, (O3) is poor and Suspended Particulates (PM10) is good then Air Quality is good.

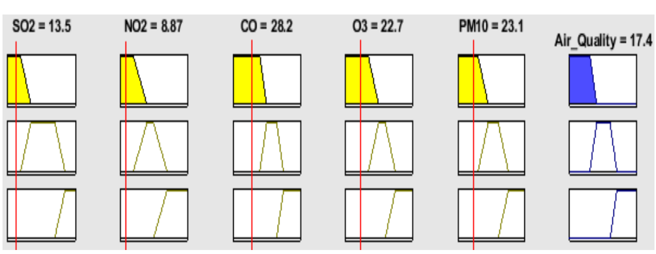


Fig. 9. Lookup diagram of Air Quality (Poor) (1).

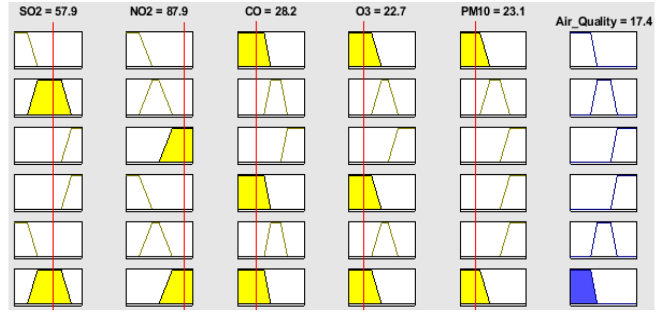


Fig. 10. Lookup diagram of Air Quality (Poor) (2).

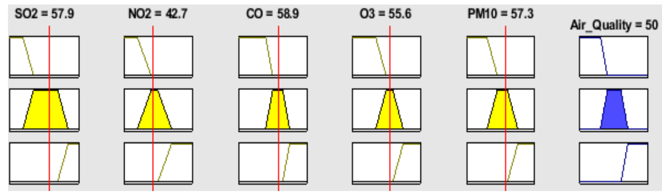


Fig. 11. Lookup diagram of Air Quality (Moderate).

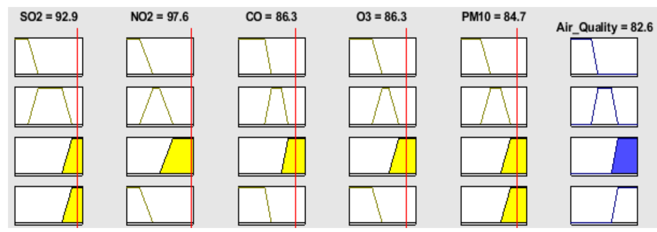


Fig. 12. Lookup diagram of Air Quality (Good) (1).

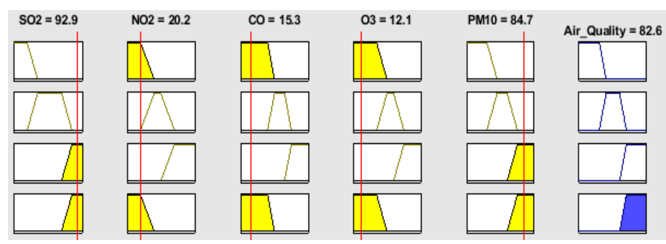


Fig. 13. Lookup diagram of Air Quality (Good) (2).

XII. Conclusion

This research work has introduced a new model based on a fuzzy inference system to monitor air quality status. The focus of this proposed research is to gather values from five atmospheric pollutants, including one particulate matter like Suspended Particulates (PM10) and four gaseous pollutants like SO2, NO2, CO, and O3 to monitor the air quality by using this proposed system. The simulation has shown that the proposed system provides better results in an efficient way to monitor air quality. Depending on the various levels of air quality, individuals can implement corresponding measures to manage and mitigate air pollution. For instance, during periods of good air quality, it indicates that the outdoor air is suitable for activities. Conversely, when the air quality is poor, precautions should be taken to minimize exposure to air pollution.

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