

Article

Fuzzy Based Prediction Model for Air Quality Monitoring for Kampala City in East Africa

Calorine Katushabe ^{1,2,*}, Santhi Kumaran ³ and Emmanuel Masabo ⁴

- ¹ African Center of Excellence in Internet of Things (ACEIoT), College of Science and Technology (C.S.T.), University of Rwanda, Nyarugenge P.O. Box 3900, Kigali, Rwanda
- ² Department of Computing, Library Science and Technology, Faculty of Agriculture, Environmental Sciences and Technology, Bishop Stuart University, Kakoba P.O. Box 09, Mbarara, Uganda
- ³ School of ICT, Copperbelt University, Kitwe P.O. Box 21692, Zambia; Santhikr69@gmail.com
- ⁴ School of ICT, College of Science and Technology, University of Rwanda, Nyarugenge P.O. Box 3900, Kigali, Rwanda; masabem@gmail.com
- * Correspondence: calorinekatushabe@gmail.com or ckatushabe@faest.bsu.ac.ug; Tel.: +256-773-298-442

Abstract: The quality of air affects lives and the environment at large. Poor air quality has claimed many lives and distorted the environment across the globe, and much more severely in African countries where air quality monitoring systems are scarce or even do not exist. Here in Africa, dirty air is brought about by the growth in industrialization, urbanization, flights, and road traffic. Air pollution remains such a silent killer, especially in Africa, and if not dealt with, it will continue to lead to health issues, such as heart conditions, stroke, and chronic respiratory organ unwellness, which later result in death. In this paper, the Kampala Air Quality Index prediction model based on the fuzzy logic inference system was designed to determine the air quality for Kampala city, according to the air pollutant concentrations (nitrogen dioxide, sulphur dioxide and fine particulate matter 2.5). It is observed that fuzzy logic algorithms are capable of determining the air quality index and therefore, can be used to predict and estimate the air quality index in real time, based on the given air pollutant concentrations. Hence, this can reduce the effects of air pollution on both humans and the environment.

Keywords: air pollution; fuzzy logic; Kampala Air Quality Index



Citation: Katushabe, C.; Kumaran, S.; Masabo, E. Fuzzy Based Prediction Model for Air Quality Monitoring for Kampala City in East Africa. *Appl. Syst. Innov.* **2021**, *4*, 44.
<https://doi.org/10.3390/asi4030044>

Academic Editor: Andrzej Białas

Received: 12 May 2021
Accepted: 15 June 2021
Published: 9 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Various cities that are industrialized and developing across the globe greatly suffer from contaminated air for the greater part of the year [1]. Dirty air has great impact globally and locally; if not paid attention to, it can become a threat to all living things, especially to humans. From the authors of [2–4], many countries in Africa have attained decades of industrialization and development but without a proper plan to handle the air pollution problem.

Many developed countries have tried to make use of current booming technologies to determine strategies and methods to improve air quality and, in the long run, mitigate the issue of air pollution but most countries in Africa still lack air pollution monitoring systems and do not have management strategies in place [5–7].

There is a great need to pay attention to air pollution concerns in Africa where urbanization and industrialization continue to increase with the increasing population density. This paper focuses on the geographical area of Kampala City in Uganda East African region where the population numbers keep increasing higher every year. Moreover, industries are being opened and also a big number of second-hand vehicles and motorcycles, which are the major sources of transport, enter into the city at higher rates annually [8].

According to the Air Visual's World Air Quality Report, Kampala city is among the cities with the most polluted air in Africa [9]. Air pollution has a great effect on health, alone causing millions of hospitalizations every year.

Major sources of air pollution in Kampala city include dust from unpaved roads and open burning of waste by individuals as a way of managing uncollected waste, which introduces dangerously large amounts of pollutants into the air via combustion. There are also massive amounts of dirty air coming from many factories and power plants around the Kampala area [10,11].

Another big contributing source of air pollution is vehicular emissions coming from many imported second-hand vehicles; the Uganda National Environment Management Authority (NEMA) estimates that more than 140,000 litres of fuel are burnt by idling cars every day in Kampala city because of ever-growing road traffic [12].

A report compiled by Global Burden of Disease project indicates that exposure to dirty air is the fifth highest ranking risk issue for death, answerable for 4.2 million deaths from heart condition and stroke, carcinoma, chronic respiratory organ unwellness, and metabolic process infections; conjointly, an extra 254,000 deaths were owing to exposure to gas and its impact on chronic respiratory organ disease around the world. In Africa alone, there was an estimated one million deaths [13].

Therefore, it's a very important health factor to measure the quality of air. Information on air quality concentrations in a particular region and its health effects is usually presented via the Air Quality Index (AQI). The AQI presents air quality concentrations in a more understandable form to the public. It is a public information tool designed to help individuals in a particular society understand the effects of air quality on both health and the environment; it is a generalized way of describing the quality of air around the universe.

In this paper, the AQI is based on Kampala standards for air quality, which follow the Environmental Protection Agency (EPA) standards [14]. The values of the Kampala Air Quality Index are divided into six groups: good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous. Different colors are assigned to each group. Thus, in this paper, the AQI prediction model for Kampala city is designed using the fuzzy logic inference system. In predicting the quality of air, traditional methods, such as clustering analysis, regression analysis and variance analysis, have been greatly used but these methods do not give the desired measurements in predicting the air quality, due to the non-linear relationship between pollutant datasets. The methods that were used in [15] included the use of an impinge air quality testing apparatus, which is very expensive and requires a huge budget, which makes it heavy and difficult for developing countries governments to fund [10]. The other approach is that samples of fine particulate matter (2.5) is collected at the end of each sampling period, stored in plastic petri dishes, sealed, and transferred to the U.S.A. for analysis.

Therefore, in this paper, a fuzzy based prediction model for predicting AQI based on the air pollutant concentrations in Kampala city is designed in order to provide the public with information about the quality of air and also the responsible authorities to take the precautions and decisions from an informed point of view of the levels of air pollutants. Fuzzy logic modeling is known to give accurate results in solving non-linear problems.

1.1. Main Air Pollutants

The AQI of Kampala is measured, following the three air pollutant concentrations in Kampala: nitrogen dioxide (NO₂), sulphur dioxide (SO₂) and particulate matter (PM_{2.5}) based on the 24 h average of hourly readings.

1.1.1. Nitrogen Dioxide

NO₂ is mainly produced in internal combustion engines burning fossil fuels, such as cars, power plants and house heaters. Direct exposure to the skin or eyes can cause irritation to the throat and nose, and it also burns. Long-term exposure to relatively low levels of nitrogen dioxide is believed to cause bronchitis and asthma, especially in children [16]. Kampala has thousands of taxis, basically used for public transport as a major means of transportation around the city.

1.1.2. Sulphur Dioxide

SO₂ is emitted through the burning of fossil fuels (for vehicles, heating, and power generation) and processing of ores containing sulphur. Exposure to SO₂ causes irritation of the eyes and lungs, causing coughing and aggravation of chronic bronchitis and asthma. Higher SO₂ levels are correlated with mortality from cardiac diseases [17].

Kampala city has a high number of vehicle growth and most of them are old fleets driven with dirty fuel on a poorly planned public transport system and road network [18].

1.1.3. Particulate Matter (PM)

PM refers to a type of air pollutants which consist of a complex mixture of particles suspended in the air, with various sizes and compositions. They are produced by both natural and anthropogenic activities. The main sources of particulate pollution are industrial activities, power plants, motor vehicles, construction activity, fires and natural windblown dust. The major industries in Kampala include the following: sugar, brewing, tobacco, cotton textiles, cement and steel production [19]. PM mass concentration is typically tracked as both PM₁₀, the total mass of PM with a diameter of 10 micrometres or less, and PM_{2.5}, the total mass of PM with a diameter of 2.5 micrometers or below (and a subset of PM₁₀). This paper concentrated mainly on PM_{2.5}, nitrogen dioxide and sulphur dioxide.

2. Materials and Methods

In this study, a simulation based on fuzzy logic techniques embedded within the MATLAB version R2017b software simulation environment was applied. In order to simulate the proposed model, the MATLAB Fuzzy Logic toolbox was used. Then, the fuzzy prediction model was modeled and its performance behavior was observed, using a set of three input parameters: indices of PM_{2.5}, indices of SO₂ and indices of NO₂. The estimated Kampala Air Quality Index (KAQI) was considered as the output parameter. In order to process the fuzzy logic model, a rule-based Mamdani's fuzzy inference system was used and later, defuzzification processes followed.

2.1. Fuzzy Modeling Approach

2.1.1. Description of Fuzzy Logic

In traditional logic, the degree of truth can be represented by either the values of 1 (true) or 0 (false), but this has limitations because some elements' membership is unclear, thereby rendering traditional methods incapable of handling complex environmental problems that have some kind of vagueness in them. In a crisp set, an element is either a member of the set or not, but also crisp elements can belong to more than one set, for example, height measurements. Therefore, fuzzy logic comes in to cater to fuzziness in solving real-life problems. In fuzzy logic, the degree of truth ranges between 0 and 1, both inclusive. Fuzzy sets allow elements to be partially in a set.

Fuzzy logic helps to compute linguistic variables, that is, variables whose values are not numbers but words or sentences in natural or artificial languages as proposed by Dr. Loft Zadeh of the University of California in the 1960s [20]. According to Banks [21], fuzzy logic can efficiently handle soft computing complex issues. Its techniques have been widely applied in all aspects of today's society, such as industrial manufacturing, diagnosis, automation control, academic education and forecasting. A linguistic variable is a collection of five things represented as $\langle T(x), U, G, M \rangle$ where

x is a variable name

$T(x)$ is a set of terms;

U is universe of discourse;

G is set of syntax rules;

M is a set of semantic rules.

Fuzzy logic works well in designing non-linear complex control solutions with multiple parameters because of the following [22]:

- Fuzzy logic has the ability to describe systems in terms of a combination of numeric and linguistic means.
- Fuzzy logic measures the certainty or uncertainty of the membership of an element of the set.
- Fuzzy algorithms are often robust in the sense that they are not very sensitive to changing environments and erroneous or forgotten rules.

In the other words, the fuzzy logic method shows the satisfactory value of air pollutants in a continuous value between 0 and 1. Fuzzy logic uses if-then implication reference rules with suitable linguistic description rules. A fuzzy rule is written as **if situation, then conclusion** [23]. In this case, the situation is also called rule premise or antecedent. The conclusion part is called consequence or conclusion, that is, IF the "antecedent" is satisfied, THEN the "consequent" is inferred.

Therefore, the designed rules are inferred, according to the fuzzy inference knowledge base to generate a generic, fuzzy based algorithm. Then, the model designed as the output represents the fuzzy function to predict the Air Quality Index for Kampala city.

2.1.2. The Proposed Fuzzy Logic Control Model

The proposed prediction model is based on fuzzy control model reasoning to predict the Kampala Air Quality Index as a percentage of the given air pollutant status. For the simulations, we used MATLAB R2017b, an environment where the fuzzy toolbox logic controller is embedded.

The fuzzy control model is designed predict the KAQI based on a set of predefined parameters, which include NO_2 , SO_2 and $\text{PM}_{2.5}$.

To build the fuzzy logic system, the principle steps are followed as shown in Figure 1. The design steps included during design are as follows: defining the input variables, fuzzyfication, formulation of fuzzy inference rules, defuzzification and model evaluation.

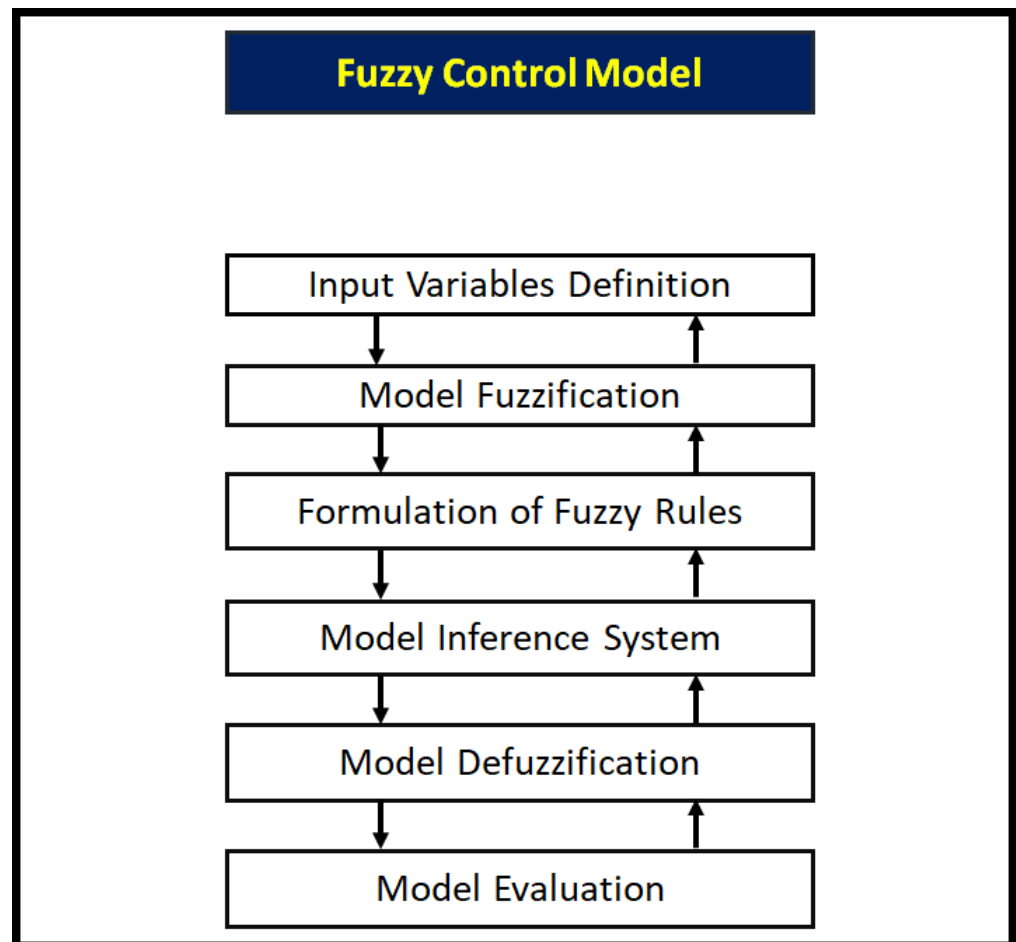


Figure 1. Main components of fuzzy model designed.

2.2. Defining the Input Variables and Fuzzyfication of the Values

In this paper, the KAQI model is designed on the basis of concentration levels of pollutants based on the Environmental Protection Agency air quality index guidelines.

As shown in Figure 2, AQI ranges from 0 to 500 and is divided into five levels: good, 0–50; moderate, 51–100; unhealthy for sensitive groups, 101–150; unhealthy, 151–200; very unhealthy, 201–300; and hazardous, 301–500.

The higher the AQI value, the poorer the quality of air; the lower the AQI value, the better the quality of air. The three input crisp parameters used to define air quality in this paper include the following: nitrogen dioxide (NO_2), sulphur dioxide (SO_2) and particulate matter ($\text{PM}_{2.5}$). The output of the system is taken as KAQI. The inputs are taken in the form of linguistic variables as well as the output.

Air Quality Index (AQI) Values	Levels of Health Concern	Colors
<i>When the AQI is in this range:</i>	<i>...air quality conditions are:</i>	<i>...as symbolized by this color:</i>
0 to 50	Good	Green
51 to 100	Moderate	Yellow
101 to 150	Unhealthy for Sensitive Groups	Orange
151 to 200	Unhealthy	Red
201 to 300	Very Unhealthy	Purple
301 to 500	Hazardous	Maroon

Figure 2. Air Quality Index guidelines [24].

2.2.1. Selection of Membership Functions

A membership function (MF) is a function that specifies the degree to which a given input belongs to a set [25]. The output of a membership function is also known as the degree of the membership function, where its value is always limited to between 0 and 1. Membership functions are used in the fuzzification and defuzzification processes to map the non-fuzzy input values to fuzzy linguistic terms and vice versa.

The Mamdani Fuzzy Logic Toolbox has many inbuilt membership functions.

In this paper, the triangular membership function, known as (trimf), is applied in the design of the proposed fuzzy based prediction model. The triangular membership function is computationally efficient and is used to normalize crisp inputs.

The Mamdani Fuzzy Inference System is suitable for designing AQI prediction models, as both the inputs and outputs of the Fuzzy Inference Systems are represented by the values of linguistic variables [26]. In order to transform crisp input values into fuzzy values, the membership function for each input is determined.

The corresponding fuzzy membership values in this paper are defined as follows:

The intensity of nitrogen dioxide (ΔNO_2) = Low, Medium and High

The intensity of sulphur dioxide (ΔSO_2) = Low, Medium and High

The intensity of particulate matter 2.5 ($\Delta\text{PM}_{2.5}$) = Low, Medium and High

The KAQI is defined and estimated as the output by the following membership values: good, moderate, sensitive, unhealthy, very unhealthy, hazardous.

2.2.2. Formulation of Fuzzy Rules

In fuzzy logic, rules play an important role. They determine the input and output membership functions that are later used in inference process. They are represented by a generic form of if–then. A fuzzy rule maps a condition described by linguistic variables and fuzzy sets to a desired output.

To design the model, the boundary values of the universal sets for the input and output variables are determined.

The fuzzy sets to be defined in universes for the fuzzification process are identified. As shown in Table 1, the boundary values of universal sets are set. Each variable is represented by three different fuzzy sets, 'Low', 'Medium', and 'High' in these universes [27].

Table 1. The boundary values of the air quality pollutants.

Index Class	AQI	NO ₂ (ppb)	SO ₂ (ppb)	PM _{2.5} (µg/m ³)
Good	0–50	0–53	0–35	0–12.0
Moderate	51–100	54–100	36–75	12.1–35.4
Sensitive	101–150	101–360	76–185	35.5–55.4
Unhealthy	151–200	361–649	186–304	55.5–150.4
Very Unhealthy	201–300	650–1249	305–604	150.5–250.4
Hazardous	301–500	1250–2049	605–1004	250.5–500.4

In order to determine the boundary values for ‘Low’, ‘Medium’ and ‘High’ fuzzy sets, the corresponding boundary values of the sets are defined in the form of ‘Good’, ‘Moderate-Sensitive’, ‘Unhealthy-Very-Unhealthy-Hazardous’ and fuzzy set values are defined based on the lower and upper boundary values for the universal sets.

In this work, the values are defined following the boundaries indicated by the Environmental Protection Agency (EPA) standards [14].

EPA is an international agency that prescribes standards and guidelines relating to air pollution as elaborated in Figure 2 [28].

Table 2 shows the boundary values of universal sets and fuzzy sets NO₂, SO₂, and PM_{2.5} input variables. The membership functions for the input variables fuzzy sets are defined basing on the boundary values.

Table 2. The boundary values of crisp sets and fuzzy sets for input parameters, domain ranges, universe of discourse membership function.

Crisp Input Variables	Fuzzy Input Parameters	Boundary Values for Universal Sets	Universe of Discourse for MFs
NO ₂ (ppb)	Low, Medium, High	0–2049	0–53, 54–360, 361–2049
SO ₂ (ppb)	Low, Medium, High	0–1004	0–75, 76–304, 305–1004
PM _{2.5} (µg/m ³)	Low, Medium, High	0–500.4	0–12.0, 12.1–55.4, 55.5–500.4

The selected output variable is KAQI and is represented by the six fuzzy sets, ‘Good’, ‘Moderate’, ‘Sensitive’, ‘Unhealthy’, ‘Very Unhealthy’ and ‘Hazardous’. The boundary values of these output fuzzy sets are determined by considering the value ranges used by the Environmental Protection Agency standards as indicated in Table 3.

Table 3. The boundary values of crisp sets and fuzzy sets for output parameters, domain ranges, universe of discourse membership function.

Input Variables	Fuzzy Input Parameters	Boundary Values for Universal Sets	Universe of Discourse for MFs
KAQI	Good, Moderate, Sensitive, Unhealthy, Very Unhealthy, Hazardous	0–500	0–50, 51–100, 101–150, 151–200, 201–300, 301–500

In Table 4, the relationship between the input variables and output variables is determined by the rule base.

The fuzzy associative memory method is used to map input fuzzy values to corresponding output fuzzy sets in order to generate the inference rules. In this, the three variables represented by the three fuzzy sets, a total of twenty-seven rules, are generated in the following rule base: for 3 inputs (M) classified into 3 linguistic variables (N). M to the power N rules ($M^N = 3^3$) are generated. Rules are formed based on the highest values of NO₂, SO₂ and PM_{2.5}. To generate the rule base, we take into consideration all the pollutant concentrations, that is, if one of the pollutants is high, then the resultant KAQI will be Unhealthy, as clearly indicated in the rule base.

Table 4. FIS Rule base for NO₂, SO₂, PM_{2.5}.

Rule No.	NO ₂ (ppb)	SO ₂ (ppb)	PM _{2.5} (µg/m ³)	KAQI
1	Low	Low	Low	Good
2	Low	Low	Medium	Moderate
3	Low	Medium	High	Unhealthy
4	Low	Medium	Low	Moderate
5	Low	Medium	Medium	Sensitive
6	Low	Medium	High	Very Unhealthy
7	Low	High	Low	Unhealthy
8	Low	High	high	Very Unhealthy
9	Medium	High	High	Very Unhealthy
10	Medium	Low	Low	Moderate
11	Medium	Low	Medium	Sensitive
12	Medium	Low	High	Unhealthy
13	Medium	Medium	Low	Moderate
14	Medium	Medium	Medium	Moderate
15	Medium	Medium	High	Very Unhealthy
16	Medium	High	Low	Very Unhealthy
17	Medium	High	Medium	Very Unhealthy
18	Medium	High	High	Hazardous
19	High	Low	Low	Unhealthy
20	High	Low	Medium	Unhealthy
21	High	Low	High	Hazardous
22	High	Medium	Low	Unhealthy
23	High	Medium	Medium	Very Unhealthy
24	High	Medium	High	Hazardous
25	High	High	Low	Hazardous
26	High	High	Medium	Hazardous
27	High	High	High	Hazardous

3. Results

3.1. The Fuzzy Control System Design

As observed in Figure 3, the design of the fuzzy based air quality index prediction model is designed using the Fuzzy Toolbox and the Mamdani FIS, integrated within the MATLAB environment. It illustrates how different air pollutants affect the Air Quality Index.

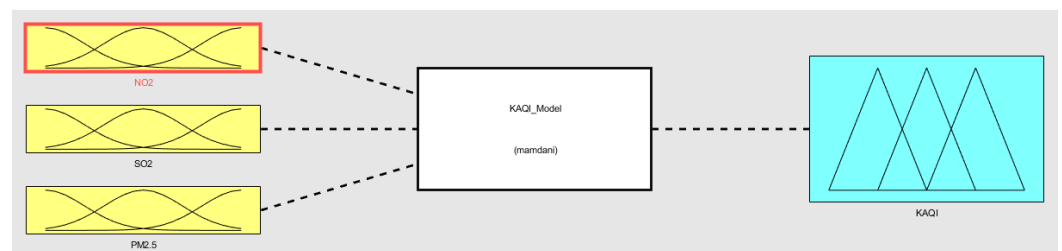


Figure 3. Design of the Air Quality Index prediction model for NO₂, SO₂ and PM_{2.5} vs. KAQI.

3.2. Designs of the Input/Output Fuzzy Membership Functions

From Figure 3, illustration of the sample input/output designs for the fuzzy inference systems variables and their respective membership functions plots are indicated.

In Figures 4–6 the triangular type membership function designed plots for NO₂, SO₂ and PM_{2.5} are indicated. For instance, Figure 4 illustrates the fuzzy inference system for input variables for NO₂ (Low, Medium, and High) and its corresponding membership function plot. Additionally, the estimated KAQI as an output variable is illustrated in Figure 7.

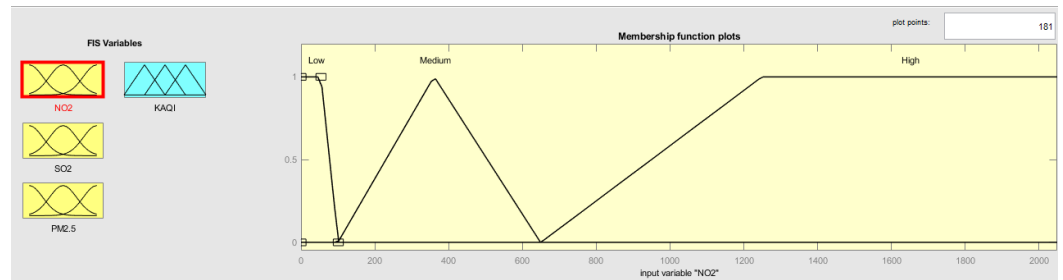


Figure 4. NO₂ input variable.

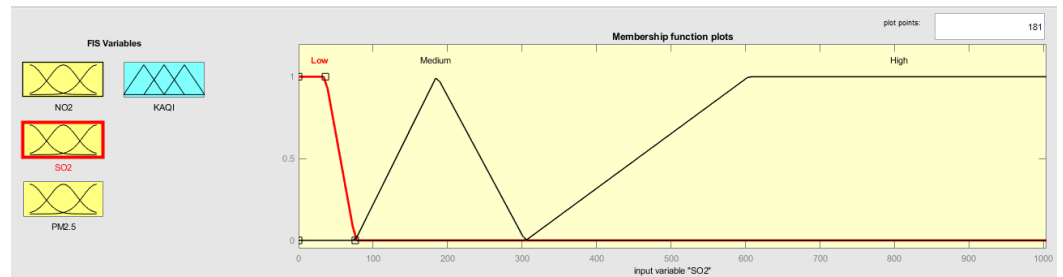


Figure 5. SO₂ input variable.

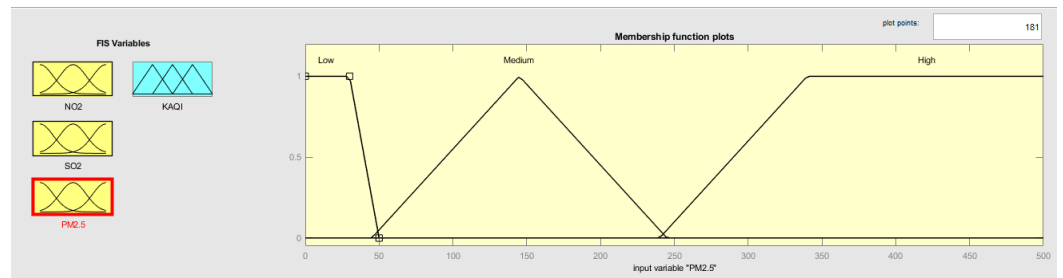


Figure 6. PM_{2.5} input variable.

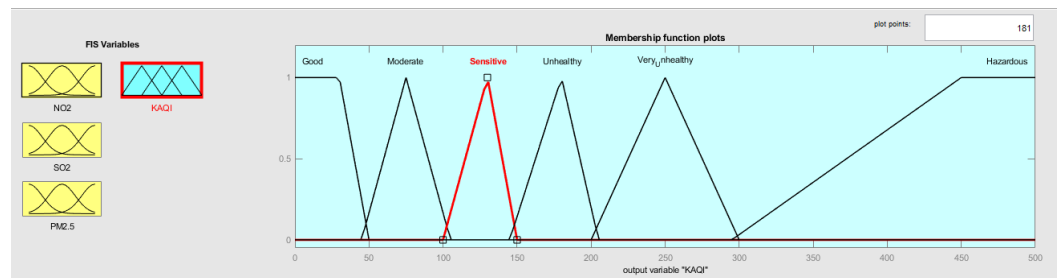


Figure 7. KAQI output variable.

3.3. Evaluation of the Proposed Fuzzy Based KAQI Prediction Model

In this section, the proposed fuzzy inference rules that were used in the output evaluation of the proposed fuzzy based KAQI prediction model are captured as shown in Figure 8. The “AND” connector is applied in designing the inference rules and it is important in determining the minimum concentration levels of the estimated Air Quality Index, given a set of fuzzy input parameters as already discussed.

In the model evaluation, all the fuzzy inference rules are considered to have an equal weighted priority function ($W = 1$). This means that all rules have equal priority during model evaluation and therefore, the order does not matter.

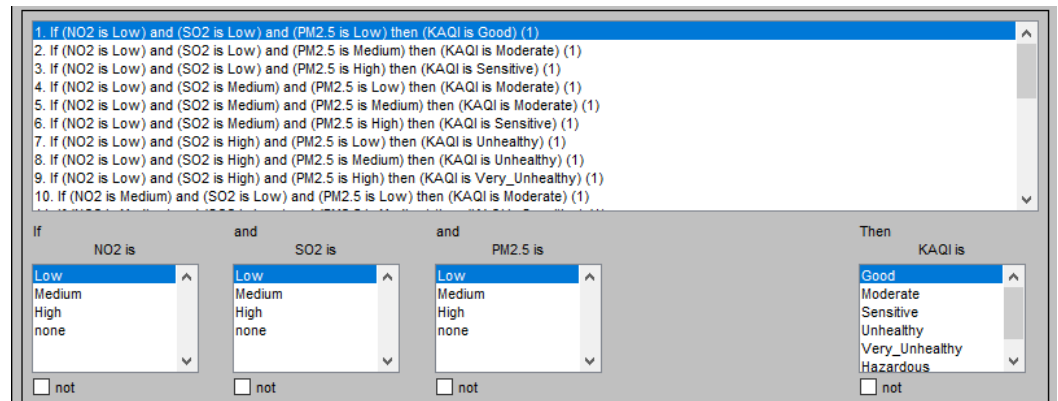


Figure 8. MATLAB evaluation inference rules editor view design for NO₂, SO₂, PM_{2.5} vs. KAQI.

3.4. Rule and Surface Viewer

The rule viewer is used in the fuzzy inference diagram. It is used as a diagnostic tool to see, for instance, which rules are active, or how individual membership function influences the results.

Figure 9 shows how air pollutants NO₂, SO₂ and PM_{2.5} concentration levels greatly affect the Kampala Air Quality Index in the rule view. For example, the figure demonstrates the resultant Air Quality Index, given the concentration values of the air pollutants NO₂, SO₂ and PM_{2.5}; if NO₂ = 30 ppb, SO₂ = 50 ppb and PM_{2.5} = 20.9 µg/m³, then the predicted KAQI = 27.

As indicated in Figure 10, the surface viewer is used to view the dependency of one of the outputs on any one or two of the inputs, that is, it generates and plots an output surface map for the model. In this case, the surface view shows how the output KAQI is dependent on the air pollutant, NO₂, SO₂ and PM_{2.5}, concentrations. A change in any of the air pollutant concentrations affects the KAQI. The plot also shows the relation between the air pollutants and the Air Quality Index and it is seen that when there is an increase in any of the air pollutant input concentrations, there is an increase in the KAQI, irrespective of the other values of the air pollutant values.



Figure 9. Active rules and Membership functions of input NO₂, SO₂, PM_{2.5} vs. output of KAQI.

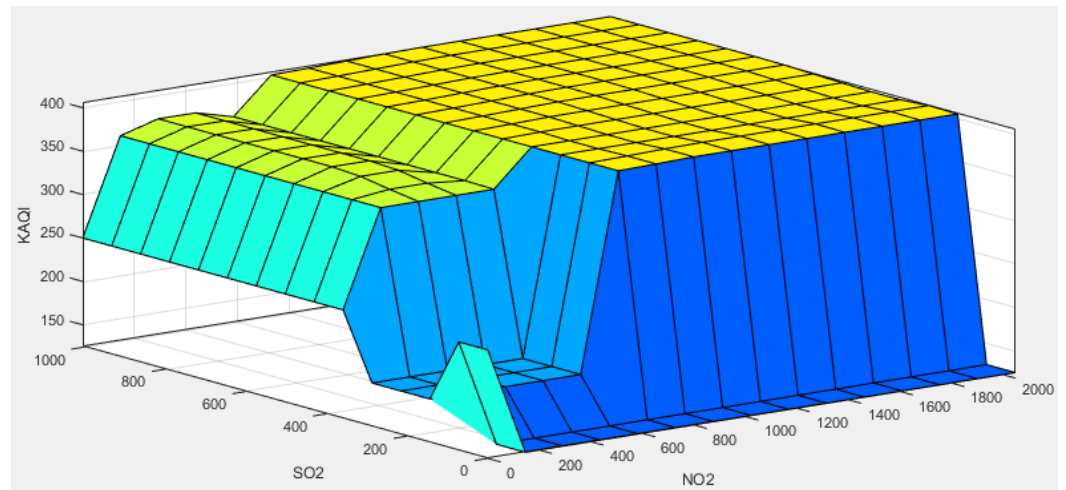


Figure 10. Surface view of the KAQI in Fuzzy Inference System.

3.5. Defuzzification to Crisp Sets

Defuzzification is the process of converting a fuzzified output into a single crisp value with respect to the fuzzy set in order to generate a readable output. The defuzzified process in the Fuzzy Inference System controller represents the action to be taken in controlling the process. There are various defuzzification methods, and each outputs a different result. A method is chosen depending on the nature of the problem that is being solved.

Therefore, in this study, the Center Of Gravity (COG) method is used because of it being the most commonly used method among others, such as the mean of maxima method, maximum membership principle method and weighted average method. COG gives a more accurate result compared to the rest of the other methods because it finds the value that corresponds to the center of gravity of the curve obtained [29].

To calculate the output crisp value in this work using the COG, assuming “Z” is “C”, then the formula for the expression is formulated as follows, where Z is the final output KAQI:

$$Z = \frac{\int \mu_C(Z)Z dz}{\int \mu_C(Z) dz} \tag{1}$$

Therefore, the defuzzified value of the output for the input values of SO₂ = 30 ppb, NO₂ = 50 ppb, and PM_{2.5} = 20.9 µg/m³ is the predicted KAQI = 27 as shown in Figure 9.

4. Discussion

Performance Evaluation of the Designed KAQI Prediction Model

After simulating and modeling the proposed model successfully, an evaluation performance is carried out by a comparative analysis of prediction, using the conventional method and the fuzzy logic based method.

To carry out the comparative analysis, first, the Air Quality Index is calculated based on the linear interpolation formula below.

$$I_p = \frac{I_{high} - I_{Low}}{B_{PHigh} - B_{PLow}} (C_p - B_{PLow}) + I_{Low} \tag{2}$$

where,

I_p = the index for pollutant *p*

C_p = is the monitored concentration of pollutant *p*

B_{PHigh} = the breakpoint that is greater than or equal to C_p

B_{PLow} = the breakpoint that is less than or equal to C_p

I_{High} = the AQI value corresponding to $BPHigh$
 I_{Low} = the AQI value corresponding to $BPLow$

The linear interpolation method is used for determining the short and long term air quality indices, and it is used to estimate and predict unknown values for any geographic point data, such as rainfall, noise pollution and air pollutant concentrations [30].

In this study, air pollutant values for NO_2 , SO_2 and $PM_{2.5}$ are picked randomly from the data, which are collected from an open source and later used to test and evaluate the model. For instance, if the value of NO_2 is 290 ppb, SO_2 is 350 ppb and $PM_{2.5}$ is $300 \mu g/m^3$, then, using the linear interpolation method to calculate the KAQI, each pollutant is calculated and the highest individual pollutant index out of them all represents the KAQI as shown in the calculation below.

$$\begin{aligned} \text{Index for pollutant } NO_2 &= (300 - 201/360 - 101) \times (290 - 101) + 201 \\ &= (99/259) \times 189 + 201 \\ &= 273 \end{aligned}$$

$$\begin{aligned} \text{Index for pollutant } SO_2 &= (500 - 301/604 - 305) \times (350 - 305) + 301 \\ &= (199/299) \times 45 + 301 \\ &= 331 \end{aligned}$$

$$\begin{aligned} \text{Index for pollutant } PM_{2.5} &= (300 - 201/500.4 - 250.5) \times (300 - 250.5) + 201 \\ &= (99/249.9) \times 49.5 + 201 \\ &= 220.6 \end{aligned}$$

Therefore, KAQI becomes 331, whereas when the same data are fed into the Fuzzy Inference System, the model produces the result of 361.

Table 5 shows some of the observations that are made to compare the logic and linear interpolation method performance corresponding to SO_2 , NO_2 and $PM_{2.5}$ concentrations. It is observed that fuzzy gives satisfactory results and this makes it a great approach to significantly estimate the KAQI.

Table 5. Comparative Analysis of KAQI determined by fuzzy logic and linear interpolation methods corresponding to SO_2 , NO_2 and $PM_{2.5}$ concentrations.

No. of Observations	$NO_{2.5}$ (ppb)	$SO_{2.4}$ (ppb)	$PM_{2.5}$ ($\mu g/m^3$)	KAQI Using Fuzzy Logic Based Model	KAQI Using Linear Interpolation Method
1	30	50	20.9	27	18
2	40	185	150	250	200
3	100	150	30.6	80	134
4	290	350	345	361	331

When a graph is plotted for further comparative analysis between fuzzy logic and linear interpolation approaches to determine the KAQI, a strong correlation is observed between both methods as shown in Figure 11.

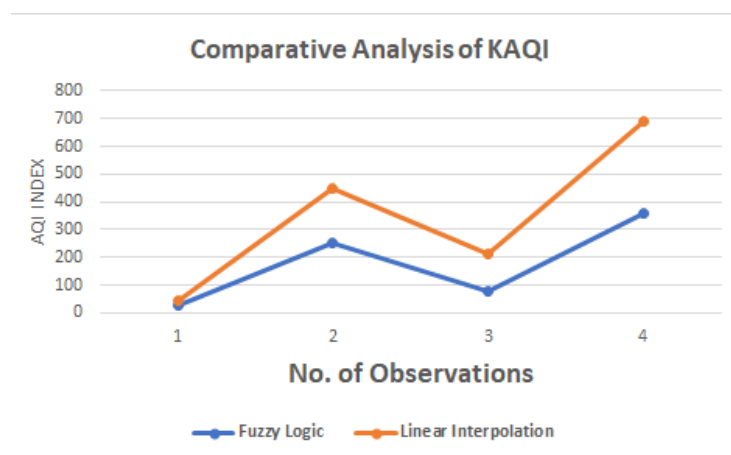


Figure 11. Comparative analysis of KAQI.

5. Conclusions

In this paper, KAQI prediction model based on the fuzzy logic inference system was designed to predict the air quality for Kampala city, according to the air pollutant data concentrations. It was observed that fuzzy logic algorithms are capable of determining the Air Quality Index and therefore, can be used to predict and estimate the Air Quality Index in real time, based on the given air pollutant concentrations. Hence, this can reduce the effects of air pollution on both humans and the environment.

Author Contributions: Methodology, C.K.; formal analysis, S.K. and E.M.; software, C.K.; supervision, S.K. and E.M.; writing—original draft preparation, C.K.; review, S.K. and E.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by African Center of Excellence in Internet of Things (ACEIoT).

Acknowledgments: C.K. wishes to thank S.K. and E.M. for the numerous advice and guidance throughout the research process.

Conflicts of Interest: The authors declare that there is no conflict of interest. The funders had no role in the design of the study; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

AQI	Air Quality Index
EPA	Environmental Protection Agency
NO ₂	Nitrogen dioxide
SO ₂	Sulphur dioxide
PM _{2.5}	Particulate matter 2.5
KAQI	Kampala Air Quality Index
COG	Center of Gravity
NEMA	Uganda National Environment Management Authority
MFs	Membership Functions

References

- Onkal-Engin, G.; Demir, I.; Hiz, H. Assessment of urban air quality in Istanbul using fuzzy synthetic evaluation. *Atmos. Environ.* **2004**, *23*, 3809–3815.
- Air Pollution: Africa's Invisible, Silent Killer. Available online: <https://www.theguardian.com/global-development/2016/oct/20/air-pollution-deadlier-africa-than-dirty-water-or-malnutrition-oecd> (accessed on 8 October 2020).
- Air Pollution: Invisible Silent Killer in Africa. Available online: <https://www.unenvironment.org/news-and-stories/story/air-pollution-africas-invisible-silent-killer-1> (accessed on 14 October 2020).
- Smith, K.R.; Samet, J.M.; Romieu, I.; Bruce, N. Indoor air pollution in developing countries and acute lower respiratory infections in children. *Thorax* **2000**, *55*, 518–532.

5. Kirenga, B.; Meng, Q.; Van Gemert, F.; Aanyu, T.H.; Chavannes, N.; Katamba, A.; Obai, G.; Molen, T.; Schwander, S.; Mohsenin, V. The state of ambient air quality in two Ugandan cities: A pilot cross-sectional spatial assessment. *Int. J. Environ. Res. Public Health* **2015**, *12*, 8075–8091.
6. Schwela, D. *Review of Urban Air Quality in Sub-Saharan Africa Region: Air Quality Profile of SSA Countries*; World Bank: Washington, DC, USA, 2012.
7. Kiggundu, A.T. An assessment of the capabilities and gaps in urban air quality management in Uganda. *Sci.-Afr. J. Sci. Issues Res. Essays* **2015**, *3*, 616–668.
8. Bateebe, I.P. Investigation of Probable Pollution from Automobile Exhaust Gases in Kampala, City, Uganda. Master's Thesis, School of Industrial Engineering and Management Energy, Stockholm, Sweden 2011.
9. National Environment Management Authority. Fight Air Pollution to Protect Human Health and Environment. Available online: <https://www.newvision.co.ug/digital-assets/cf4bd175-7293-4e9a-8fba-7235c1e6b8b1/32-NEMA.pdf> (accessed on 6 December 2020).
10. Schwander, S.; Okello, C.D.; Freers, J.; Chow, J.C.; Watson, J.G.; Corry, M.; Meng, Q. Ambient particulate matter air pollution in Mpererwe District, Kampala, Uganda: A pilot study. *J. Environ. Public Health* **2014**, *14*, 763934.
11. Coker, E.; Katamba, A.; Kizito, S.; Eskenazi, B.; Davis, J.L. Household air pollution profiles associated with persistent childhood cough in urban Uganda. *Environ. Int.* **2020**, *136*, 105471.
12. Matagi, S.V. Some issues of environmental concern in Kampala, the capital city of Uganda. *Environ. Monit. Assess.* **2002**, *2*, 121–138.
13. Ambient (Outdoor) Air Quality and Health. Available online: [http://www.who.int/en/news-room/fact-sheets/detail/ambient-\(outdoor\)-air-quality-and-health](http://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health) (accessed on 15 November 2020).
14. US EPA. Technical Assistance Document for the Reporting of Daily Air Quality. Available online: <https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf> (accessed on 31 May 2021).
15. Jovanelly, T.J.; Okot, O.J.; Nyenje, R.; Namaganda, E. Comparative Assessment of Ambient Air Standards in Rural Areas to Uganda City Centers. *J. Public Health Dev. Ctries* **2017**, *3*, 371–380.
16. Robertson, S.; Miller, M.R. Ambient air pollution and thrombosis. *Part. Fibre Toxicol.* **2018**, *15*, 1.
17. Matooane, M.; Diab, R. Health risk assessment for sulfur dioxide pollution in South Durban, South Africa. *Arch. Environ. Health Int. J.* **2003**, *58*, 763–770.
18. Kwikiriza, B.C. Causes and Effects of Traffic Congestion in Kampala City. Available online: https://scholar.googleusercontent.com/scholar.bib?q=info:KUzfthKjfmAJ:scholar.google.com/&output=citation&scisdr=CgUbOhNFEPH9-0peEHk:AAGBfm0AAAAAYMxYCHmvHm_b2NLN7bA2H3SuDykPUJwR&scisig=AAGBfm0AAAAAYMxYCGwLr7IZUPsooIme4bwYyUIDd7SV&scisf=4&ct=citation&cd=-1&hl=en (accessed on 17 October 2020)
19. Eva, W.; Patrik, L.A.; Terry, B.; Christoffer, B.; Danielle, J.C.; Elena, C.; Stephania, A.C.; Sandra, C.G.; Brian, K.G.; Christer, J.; et al. 14th congress of combustion by-products and their health effects—Origin, fate, and health effects of combustion-related air pollutants in the coming era of bio-based energy sources. *Environ. Sci. Pollut. Res.* **2016**, *23*, 8141–8159.
20. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning—I. *Inf. Sci.* **1975**, *8*, 199–249.
21. Banks, W. Linguistic Variables: Clear Thinking with Fuzzy Logic. 2008. Available online: <http://www.phaedsys.com/principals/bytecraft/bytecraftdata/LinguisticVariables.pdf> (accessed on 18 December 2020).
22. Piegat, A. What Are the MAIN Advantages of Applying Fuzzy-Based Decision Making Approaches in Comparison with the Non-Fuzzy-Based Ones? 2015. Available online: https://www.researchgate.net/post/What_are_the_main_advantages_of_applying_fuzzy-based_decision_making_approaches_in_comparison_with_the_non-fuzzy-based_ones (accessed on 10 December 2020).
23. Liu, M.; Chen, D.; Wu, C.; Li, H. Approximation theorem of the fuzzy transform in fuzzy reasoning and its application to the scheduling problem. *Comput. Math. Appl.* **2006**, *51*, 515–526.
24. EPA. *Air Quality Index. A Guide to Air Quality and Your Health*; EPA: Washington, DC, USA, 2014.
25. Ali, O.A.M.; Ali, A.Y.; Sumait, B.S. Comparison between the effects of different types of membership functions on fuzzy logic controller performance. *Int. J.* **2015**, *76*, 76–83.
26. Hajek, P.; Olej, V. Air quality indices and their modelling by hierarchical fuzzy inference systems. *WSEAS Trans. Environ. Dev.* **2009**, *10*, 661–672.
27. Jain, A.; Sharma, A. Membership function formulation methods for fuzzy logic systems: A comprehensive review. *J. Crit. Rev.* **2020**, *7*, 8717–8733
28. Ruckelshaus, W.D. The Role of the Environmental Protection Agency. *Envtl. Aff.* **1971**, *1*, 528
29. Atacak, I.; Arici, N.; Guner, D. Modelling and evaluating air quality with fuzzy logic algorithm-Ankara-Cebeci sample. *Int. J. Intell. Syst. Appl. Eng.* **2017**, *5*, 263–268.
30. David, M. *Guideline for Reporting of Daily Air Quality—Air Quality Index (AQI)*; U.S. Environmental Protection Agency: Washington, DC, USA, 2006.