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Research Article

Analysis of Fuzzy Membership Function on Greenhouse Gas Emission Estimation by Triangular and Trapezoidal Membership Functions in Indian Smart Cities

Velmurugan S[1], Arun kumar S[2], Udhayakumar R[3*]

[1]Department of Mathematics, Shanmugha Arts, Science, Technology and Research Academy, Thanjavur, India
[2]Department of Mathematics, Saranathan College of Engineering, Tiruchy, India
[3]Department of Mathematics, School of Advanced Science, Vellore Institute of Technology, Vellore, India
E-mail: udhayakumar.r@vit.ac.in

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Abstract: This research aims to analyze the efficiency of triangular and trapezoidal membership functions in forecasting CO_2, N_2O, and CH_4 emissions in Indian smart cities. Over 10-years, emissions data for these gases were collected and used to determine membership values for both functions. The study evaluated the performance of the membership functions using Root Mean Square Error (RMSE) values and percentage error analysis. The results indicated that the trapezoidal membership function provided more accurate results for CO_2 and CH_4 emissions, while the triangular membership function was more accurate for N_2O emissions. These findings highlight the importance of selecting appropriate membership functions tailored to specific gases to enhance emission forecast accuracy. The study emphasizes the significance of such insights for decision-makers, urban planners, and environmental agencies involved in emissions reduction measures and smart city development. However, further research is recommended to validate these findings and explore additional factors that may influence the performance of membership functions in emission prediction in smart cities. In conclusion, this project offers a comprehensive analysis of triangular and trapezoidal membership functions' accuracy in predicting emissions in Indian smart cities, emphasizing the crucial factors.

Keywords: greenhouse gas, membership function, triangular membership function, trapezoidal membership function, root mean square error (RMSE)

MSC: 28E10, 68T27, 68T37

1. Introduction

1.1 *Climate change and its reason*

Climate change has emerged as one of the most pressing global challenges of our time. It poses significant threats to ecosystems, human health, economics, and social well-being. The primary driver of climate change is the excessive accumulation of greenhouse gases (GHGs) in the Earth's atmosphere [1, 2]. These gases, which include carbon dioxide CO_2, Methane CH_4, Nitrous oxide N_2O, and various industrial gases, act like a blanket, trapping heat and causing the planet to warm up [3]. In this introduction, The reasons behind greenhouse gas emissions and delve into the consequences

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they have on our climate system. Greenhouse gases are essential for Earth's habitability, but human activities like deforestation, industry, fossil fuel combustion, and agriculture have elevated their levels. Carbon dioxide, mainly from burning coal, natural gas, and oil, is the primary contributor, responsible for about 75% of the warming effect [4]. Methane and nitrous oxide are potent greenhouse gases, emitted from various sources including fossil fuel operations, agriculture, and industrial activities, contributing to global warming. The use of fossil fuels in transportation and industrial operations is a major contributor to greenhouse gas emissions. CO_2 is released during the extraction, refining, and combustion of coal, oil, and natural gas. The transportation sector is heavily reliant on fossil fuels, and the industrial sector emits significant CO_2 during the production of cement, steel, and other materials. These emissions have steadily increased over the past century, resulting in a significant rise in atmospheric CO_2 levels [5]. Deforestation releases stored carbon and contributes to climate change emissions and worsens the greenhouse effect, reduces Earth's CO_2 absorption capacity, harms biodiversity, disrupts ecosystems, and threatens livelihoods [6, 7]. Agriculture is a significant source of both CO_2 and non-CO_2 greenhouse gases, with methane and nitrous oxide emissions contributing one-third of total anthropogenic GHG emissions. Methane arises from enteric fermentation, animal waste management, and rice production, while nitrous oxide primarily comes from synthetic fertilizers, animal manure, and agricultural residue combustion. These emissions not only impact climate change but also degrade air and water quality. Industrial activities, including cement manufacturing, chemical production, and metal fabrication, emit various greenhouse gases. The cement sector is a major contributor to CO_2 emissions due to the release of CO_2 during limestone calcination. Chemical manufacturing produces industrial gases like hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6), which have high global warming potentials. Although emitted in smaller quantities than CO_2, their warming effects can be hundreds of times stronger.

1.2 *Real time effects*

The primary greenhouse gases (GHGs) responsible for climate change are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). These gases are significant greenhouse gas contributors, trapping heat in the Earth's atmosphere and contributing to global warming. This section will investigate the causes and consequences of CO_2, N_2O, and CH_4 emissions, as well as their contributions to climate change. Carbon dioxide (CO_2) is the most prevalent and well-known greenhouse gas. It is mostly emitted when fossil fuels such as coal, oil, and natural gas are utilized to generate energy, transport people, and conduct industrial operations. The flaming of these fossil fuels emits massive volumes of CO_2 into the atmosphere, which accumulates over time. Deforestation and changes in land use can contribute to CO_2 emissions because trees operate as carbon sinks, absorbing CO_2 through photosynthesis. When forests are removed, the carbon that has been stored in them is released back into the atmosphere [8]. The fundamental cause of anthropogenic climate change is an increase in atmospheric CO_2 levels, which accounts for around three-quarters of the warming impact. It is a long-lasting gas that may be present in the atmosphere for millennia, and its concentration is rising at an alarming rate.

Methane (CH_4) is the second most important greenhouse gas in terms of warming potential. It is produced, transported, and used in the production, transportation, and consumption of coal, oil, and natural gas. CH_4 is also released by agricultural operations such as enteric fermentation in ruminant animals (cattle, sheep, and goats) and livestock waste management. Furthermore, CH_4 is produced during the breakdown of organic waste in landfills, as well as during the production and transport of coal, oil, and gas. Although methane has a shorter lifetime in the atmosphere than CO_2, Methane (CH_4) is the second most potent greenhouse gas in terms of warming potential. It is more effective at trapping heat, making it a strong greenhouse gas. CH_4 has around 28-36 times the warming potential of CO_2 over a 100-year timescale. The concentration of methane in the atmosphere has been gradually increasing, and its important impact on climate change cannot be overlooked. significant greenhouse gas emissions.

Nitrous oxide (N_2O) is predominantly produced by agricultural and industrial processes. N_2O is released in agriculture as a result of the management of livestock waste, the growing of rice, and mostly the use of synthetic fertilizers. The flaming of fossil fuels, biomass, and also Nitrous oxide emissions are produced by solid waste. N_2O emissions are also produced by industrial activities such as the manufacture of chemicals and the combustion of fossil fuels. Nitrous oxide is also one of the long-lasting greenhouse gas, with an estimated lifetime of 114 years. Over a 100-year period, it has a warming potential that is approximately 265-298 times that of CO_2 [9]. While N_2O contributes less to overall greenhouse gas emissions than CO_2 and CH_4, its potency as a greenhouse gas makes it a major contribution to climate change.

The consequences of these greenhouse gas emissions, particularly CO_2, CH_4, and N_2O, are far-reaching. Rising CO_2 levels contribute to the warming of the Earth's surface, leading to a range of impacts such as sea-level rise, melting polar ice caps and glaciers, and rising global temperatures. These changes disrupt ecosystems, endanger wildlife, and pose risks to human populations, particularly those in vulnerable coastal areas. Methane emissions not only contribute to global warming but additionally, they contribute to the development of ground-level ozone, a dangerous air pollutant. This can have adverse effects on human health, leading to respiratory problems and exacerbating existing conditions such as asthma.

Furthermore, agricultural methane emissions can have both environmental and economic effects. Methane generated by enteric fermentation and animal waste management contributes to the agriculture sector's overall greenhouse gas footprint. Methane emissions not only cause climate change but also constitute a waste of precious energy [10]. Technologies for methane capture and use can assist reduce emissions while also offering a renewable energy source.

Emissions of nitrous oxide contribute to both climate change and air pollution. In addition to its high warming potential, N_2O contributes significantly to ozone layer depletion. Increased nitrous oxide levels in the atmosphere lead to the breakdown of ozone molecules, resulting in ozone layer depletion and an increased risk of harmful ultraviolet (UV) radiation reaching the Earth's surface. High quantities of this kind of radiation can be harmful to human health, including an increased risk of skin cancer and eye impairment. Furthermore, nitrous oxide emissions can cause eutrophication of bodies of water, altering aquatic ecosystems and depleting oxygen in aquatic environments.

To address the issues posed by these greenhouse gases, comprehensive policies, and worldwide collaboration are required. Transitioning to cleaner and more sustainable energy sources, improving energy efficiency, and encouraging the use of renewable technology are all part of efforts to minimize carbon dioxide emissions. Forest conservation and replanting programs must be promoted in order to reduce CO_2 emissions by protecting carbon sinks [11]. Furthermore, sustainable land management practices and reduced deforestation are critical for limiting CO_2 emissions from land-use changes.

Improving agricultural practices, such as developing more efficient livestock farming methods, implementing better waste management systems, and increasing the use of renewable energy for waste treatment, can all assist to minimize methane emissions. Methane leaks from oil and gas infrastructure, as well as the management of methane emissions from coal mining, may both significantly contribute to methane mitigation initiatives [12]. Adopting more sustainable agricultural practices, such as optimizing fertilizer usage, using precision agriculture techniques, and encouraging the use of alternate nitrogen sources, is required to reduce nitrous oxide emissions. Efficient manure management systems and the use of anaerobic digestion technology can aid in the absorption of methane emissions from livestock operations, lowering both CH_4 and N_2O emissions.

Furthermore, international treaties such as the Paris Agreement are critical in developing global collaboration and commitment to lowering greenhouse gas emissions. Countries may work together to mitigate the effects of CO_2, CH_4, and N_2O emissions by implementing mitigation policies, developing and deploying clean technology, and supporting climate adaptation activities.

In conclusion, the principal contributors to greenhouse gas-induced climate change are methane, nitrous oxide, and carbon dioxide emissions. Various gases that are released as a result of numerous human activities have far-reaching repercussions for our world. Understanding the causes and consequences of these emissions allows us to devise effective methods to reduce their effects, move to more sustainable practices, and protect our planet's future [13]. Addressing greenhouse gas emissions is a global duty that will necessitate joint efforts in order to create a more sustainable and resilient future.

1.3 *Introduction on forthcoming analysis*

In this work, the goal is to evaluate the efficacy of various membership functions, notably triangular and trapezoidal, in modeling and forecasting CO_2, N_2O, and CH_4 emissions in chosen smart cities in India. The study attempts to evaluate the accuracy and usefulness of these membership functions in capturing the patterns and trends of GHG emissions over a ten-year period by analyzing emissions data. To do this, data on CO_2, N_2O, and CH_4 emissions will be gathered and analyzed for the smart cities chosen. The membership values for each emission type will be evaluated using triangular and trapezoidal membership functions. To test the correctness of the membership functions in capturing real emissions data, the Root Mean Square Error (RMSE) will be computed. The study is to identify whether the membership function works better in expressing emissions data by comparing RMSE values and analyzing percentage errors. This assessment will shed light on the feasibility and efficacy of various membership functions in modeling GHG emissions in smart cities. The outcomes of this study will help policymakers, urban planners, and academics aiming to achieve sustainability goals in smart city programs better understand the efficacy of membership functions in modeling GHG emissions [14]. The findings will contribute to the creation of effective methods to reduce emissions and promote sustainable urban development in the context of India's smart cities.

2. Materials and methods

2.1 *Fuzzy logic and fuzzy sets*

Fuzzy logic is a mathematical framework for dealing with uncertainty and imprecision in thinking and decision-making. It employs fuzzy sets and fuzzy numbers to deal with ambiguous or hazy information. In this part, look into fuzzy logic, fuzzy numbers, and fuzzy sets, as well as present examples of how they might be used in practice. It is a Boolean logic extension that allows for degrees of truth between true and false. In contrast to classical binary logic, which functions in an all-or-nothing fashion, fuzzy logic introduces the idea of partial truth. It recognizes that the veracity of a statement might range from entirely true to absolutely untrue [15, 16]. To deal with imprecise information, fuzzy logic utilizes fuzzy rules, fuzzy sets, and linguistic variables. Linguistic variables represent input and output values using linguistic words (such as "high", "medium", or "low") that mirror human perceptions and natural language. Fuzzy sets indicate an element's progressive membership in a set, allowing for degrees of membership rather than strict binary classification.

Fuzzy numbers are a type of real number that allows for some degree of ambiguity or imprecision in its values. A fuzzy integer's degree of membership throughout its range is specified by the membership function. To indicate varying degrees of confidence or ambiguity, the membership function might assume various forms, such as triangular, trapezoidal, or Gaussian. When dealing with data that is intrinsically ambiguous or subjective, fuzzy numbers come in handy. Offer a mathematical framework for gathering and manipulating imprecise data, allowing for more realistic modeling and decision-making in uncertain contexts [17]. Fuzzy sets are the foundation of fuzzy to express and handle imprecise or uncertain notions. Unlike crisp sets in classical set theory, which have either true or false membership, fuzzy sets have membership degrees ranging from 0 to 1. A membership function defines fuzzy sets by assigning a membership degree to each element in the set [18]. The membership function can have several shapes depending on the nature of the set and the underlying concept being represented, such as triangular, trapezoidal, or sigmoidal [19].

2.2 *Fuzzy membership function*

A membership function is a mathematical representation that gives each element in a fuzzy set a degree of membership. It specifies how much a specific member belongs to a given set, allowing it to describe fuzzy or unclear notions. Membership functions are important in fuzzy logic systems because identify the extent to which an element meets a specific criterion or feature [20]. Depending on the nature of the fuzzy set and the individual application, membership functions can assume various forms such as triangular, trapezoidal, Gaussian, or sigmoidal. These functions convert input values to membership degrees, which are commonly represented by integers ranging from 0 to 1. A membership value of 1 denotes complete membership, whereas several 0 indicates no membership. Membership functions to depict the gradual transition between different degrees of membership inside a fuzzy collection. To describe and reason about real-world occurrences in a more nuanced and realistic manner by providing a flexible technique to handle uncertain or imprecise notions. Membership functions can be tailored to the unique issue area and the available knowledge about the notion being represented in practice. Depending on the nature of the fuzzy set and the individual application, other shapes such as triangular, trapezoidal, or Gaussian might be utilized. Each membership function has its form and mathematical representation in fuzzy logic systems, which may be customized depending on unique applications and requirements.

2.3 *Singleton membership function*

A singleton membership function is one in which the membership value is either 0 or 1, suggesting a crisp membership. In other words, the element either fully or does not belong to the fuzzy set (membership value of 1). When dealing with crisp or exact values rather than imprecise or ambiguous values, singleton membership functions are employed [21]. A singleton membership function is represented from Figure 1 graphically by a vertical line segment extending from the x-axis to a membership value of 1. The x-axis location of the line corresponds to the specific value for which membership is determined.

$$\mu_A(x) = \begin{cases} 1, & \text{if } x = a \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

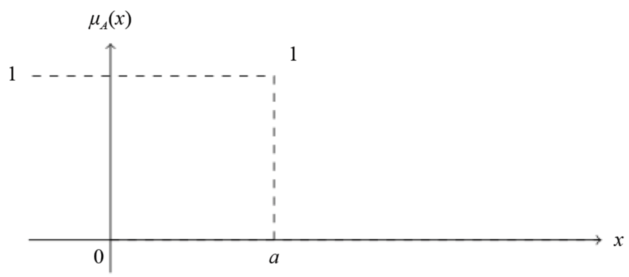

Figure 1. Singleton membership function

2.4 *Triangular membership function*

In fuzzy logic, the triangle membership function is a typical form for representing fuzzy sets. It is characterized by a triangular shape, defined by three parameters: the left boundary, the peak or center, and the right boundary. The triangular membership function allows for a gradual transition of membership values from 0 to 1 and then back to 0 [22] .

Figure 2 illustrates the triangle membership function, which has the following formula:

$$\mu_{triangular}(x) = \begin{cases} 0, & \text{if } x \leq a \\ \dfrac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ \dfrac{c-x}{c-b}, & \text{if } b < x \leq c \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Formula to evaluate the Triangular Membership Function :

$$\mu_{triangular}(x) = \max\left(0, \min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right) \tag{3}$$

where,

1. $\left(\dfrac{x-a}{b-a}\right)$: computes the degree of membership x for the triangle's increasing slope on the left.
2. $\left(\dfrac{c-x}{c-b}\right)$: computes the degree of membership x for the triangle's right decreasing slope.
3. $\min(\ldots)$: returns the number that is the smallest of the two determined membership degrees.
4. $\max(0, \ \min(\ldots)$: selects the maximum value between 0 and the smaller ratios.

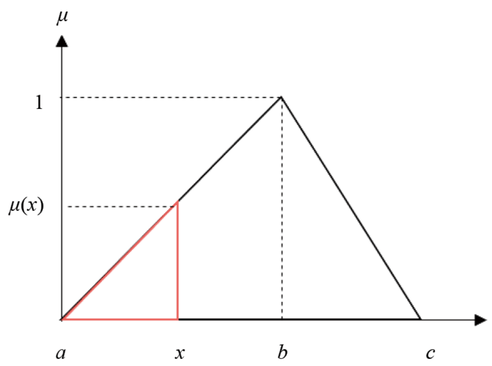

Figure 2. Triangular membership function

2.5 *Trapezoidal membership function*

Another shape widely used in fuzzy logic to describe fuzzy sets is the trapezoidal membership function. It has a trapezoidal shape that is specified by four parameters: left shoulder, left boundary, right boundary, and right shoulder. The trapezoidal membership function enables a steady movement of membership values from 0 to 1 and back to 0.

Figure 3 illustrates the trapezoidal membership function, which has the following formula:

$$\mu_{Trapezoidal}(x) = \begin{cases} 0, & \text{if } x \le a \\ \dfrac{x-a}{b-a}, & \text{if } a < x \le b \\ 1, & \text{if } b < x \le c \\ \dfrac{d-x}{d-c}, & \text{if } c < x < d \\ 0, & \text{if } x \ge d \end{cases} \tag{4}$$

When creating fuzzy sets, the trapezoidal membership function provides greater flexibility than the triangle membership function. It may depict a wider range of membership distributions and is especially effective when dealing with slow transitions or ambiguous borders. The trapezoidal membership function formula is as follows:

$$\mu_{Trapezoidal}(x) = \max\left(0, \ \min\left(\frac{x-a}{b-a}, \ 1, \ \frac{d-x}{d-c}\right)\right) \tag{5}$$

where,

1. x: input value.
2. a, b, c and d: parameters defining the trapezoidal shape.

3. $(x-a)$: evaluates the distance between the input value x and the left shoulder a.
4. $(b-a)$: evaluates the length of the left base.
5. $(d-x)$: evaluates the separation between the input value x and the right shoulder d.
6. $(d-c)$: evaluates the length of the right base.
7. The min function is used to determine the smallest ratio among the three: $\frac{x-a}{b-a}$, 1, and $\frac{d-x}{d-c}$.
8. The max function is then applied to ensure that the membership value remains within the range of 0 to 1, selecting the maximum value between 0 and the smallest ratio.

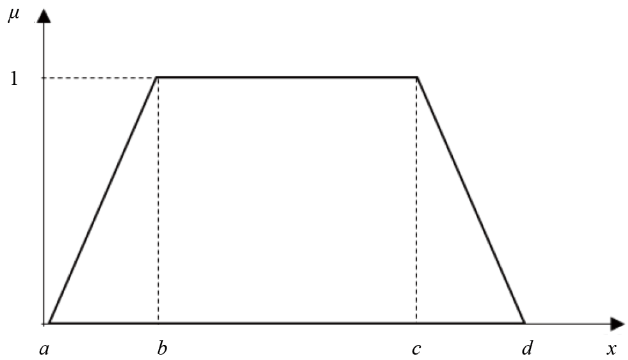

Figure 3. Trapezoidal membership function

2.6 *Root mean square error*

Root Mean Square Error (RMSE) is a well-known statistic for evaluating prediction model accuracy and performance, especially in statistics and machine learning. It computes the average magnitude of the discrepancies between expected and observed values [23–25]. RMSE is determined mathematically by evaluating the square root of the squared discrepancy between expected and actual values in a dataset of size n.

The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

In this formula:
1. n represents the number of data points.
2. y_i speak for the actual values.
3. $\hat{y}_i$ represents estimated values.

3. Results and discussion

The findings of our investigation comparing the performance of triangular and trapezoidal membership functions for assessing CO_2, N_2O, and CH_4 emissions in ten selected smart cities in India are presented and discussed in this section. To know the membership functions best in terms of minimizing the Root Mean Square Error (RMSE), which might help with smart city planning and environmental management. Estimated membership values using triangular and trapezoidal membership functions on this data. As an assessment statistic, the RMSE was utilized to demonstrate the difference between the estimated membership values and the actual emission data. To determine a better strategy for emissions modeling in smart cities by comparing the RMSE values derived from each membership function. This section describes our data-gathering approach, membership function calculation technique, use of the RMSE metric, and outcomes analysis. The findings have implications for improving emissions modeling and environmental decision-making in smart cities, as well as assisting environmental impact reduction and sustainability programs.

In the datasets source: https://business.knoema.com/datahub-access/. M represents the unit in Million metric tons. Refer the Table 1, Table 2 and Table 3.

Table 1. CO_2 (Carbon dioxide) emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	10.5 M	14.2 M	1.8 M	12.5 M	11.1 M	4.6 M	11.2 M	35.7 M	29.5 M	9.8 M
2012	10.9 M	14.6 M	1.9 M	12.9 M	11.4 M	4.8 M	11.6 M	36.3 M	30.1 M	10.2 M
2013	11.3 M	15.0 M	2.0 M	13.3 M	11.7 M	5.0 M	12.0 M	37.0 M	30.7 M	10.6 M
2014	11.7 M	15.4 M	2.1 M	13.7 M	12.0 M	5.2 M	12.4 M	37.7 M	31.3 M	11.0 M
2015	12.1 M	15.8 M	2.2 M	14.1 M	12.3 M	5.4 M	13.8 M	38.4 M	31.9 M	11.4 M
2016	12.5 M	16.2 M	2.3 M	14.5 M	12.6 M	5.6 M	13.2 M	39.1 M	32.5 M	11.8 M
2017	12.9 M	16.6 M	2.4 M	14.9 M	12.9 M	5.8 M	13.6 M	39.8 M	33.2 M	12.2 M
2018	13.3 M	17.0 M	2.5 M	15.3 M	13.2 M	6.0 M	14.0 M	40.5 M	34.0 M	12.6 M
2019	13.7 M	17.4 M	2.6 M	15.7 M	13.5 M	6.2 M	14.4 M	41.3 M	34.8 M	13.0 M
2020	14.1 M	17.8 M	2.7 M	16.1 M	13.8 M	6.4 M	14.8 M	42.1 M	35.6 M	13.4 M

Table 2. CH_4 (Methane) emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	1.3 M	1.6 M	0.8 M	1.3 M	1.4 M	1.1 M	1.5 M	1.8 M	2.1 M	1.2 M
2012	1.4 M	1.7 M	0.9 M	1.4 M	1.5 M	1.2 M	1.6 M	1.9 M	2.2 M	1.3 M
2013	1.5 M	1.8 M	1.0 M	1.5 M	1.6 M	1.3 M	1.7 M	2.0 M	2.3 M	1.4 M
2014	1.6 M	1.9 M	1.1 M	1.6 M	1.7 M	1.4 M	1.8 M	2.1 M	2.4 M	1.5 M
2015	1.7 M	2.0 M	1.2 M	1.7 M	1.8 M	1.5 M	1.9 M	2.2 M	2.5 M	1.6 M
2016	1.8 M	2.1 M	1.3 M	1.8 M	1.9 M	1.6 M	2.0 M	2.3 M	2.6 M	1.8 M
2017	1.9 M	2.2 M	1.4 M	1.9 M	2.0 M	1.7 M	2.1 M	2.4 M	2.7 M	1.9 M
2018	2.0 M	2.3 M	1.5 M	2.0 M	2.1 M	1.8 M	2.2 M	2.5 M	2.8 M	2.0 M
2019	2.1 M	2.4 M	1.6 M	2.1 M	2.2 M	1.9 M	2.3 M	2.6 M	2.9 M	2.1 M
2020	2.2 M	2.5 M	1.7 M	2.2 M	2.3 M	2.0 M	2.4 M	2.7 M	3.0 M	2.2 M

Table 3. N_2O (Nitrous Oxide) emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	1.0 M	1.2 M	0.6 M	1.0 M	1.1 M	0.8 M	1.1 M	1.3 M	1.5 M	0.9 M
2012	1.1 M	1.3 M	0.7 M	1.1 M	1.2 M	0.9 M	1.2 M	1.4 M	1.6 M	1.0 M
2013	1.2 M	1.4 M	0.8 M	1.2 M	1.3 M	1.0 M	1.3 M	1.5 M	1.7 M	1.1 M
2014	1.3 M	1.5 M	0.9 M	1.3 M	1.4 M	1.1 M	1.4 M	1.6 M	1.8 M	1.2 M
2015	1.4 M	1.6 M	1.0 M	1.4 M	1.5 M	1.2 M	1.5 M	1.7 M	1.9 M	1.3 M
2016	1.5 M	1.7 M	1.1 M	1.5 M	1.6 M	1.3 M	1.6 M	1.8 M	2.0 M	1.4 M
2017	1.6 M	1.8 M	1.2 M	1.6 M	1.7 M	1.4 M	1.7 M	1.9 M	2.1 M	1.5 M
2018	1.7 M	1.9 M	1.3 M	1.7 M	1.8 M	1.5 M	1.8 M	2.0 M	2.2 M	1.6 M
2019	1.8 M	2.0 M	1.4 M	1.8 M	1.9 M	1.6 M	1.9 M	2.1 M	2.3 M	1.7 M
2020	1.9 M	2.1 M	1.5 M	1.9 M	2.0 M	1.7 M	2.0 M	2.2 M	2.4 M	1.8 M

Here's the Evaluation of Linguistic variables :

1. Low value: The low value is normally derived as the dataset's minimal value. In this example, the population of Ahmedabad was 10.5 million in 2011. As a result, the low figure for 2011 is 10.5 million.

2. Medium value: The medium value indicates the data's center tendency. The mean is a typical measure of central tendency that is computed by adding all the values and dividing by the number of values. However, because the data reflects the population, it is preferable to use the median because it is less impacted by outliers. For the median, arrange the emission values in ascending order. 10.5 M, 10.9 M, 11.3 M, 11.7 M, 12.1 M, 12.5 M, 12.9 M, 13.3 M, 13.7 M, 14.1 M. As a result, the median value for 2012 is 12.3 M.

3. High value: The high value is normally determined as the dataset's maximum value. In this situation, the greatest reported population in Ahmedabad is 14.1 million in 2020. As a result, the high value for 2020 is 14.1 million.

To summarize:

• Low value for 2011: 10.5 M.

• Medium value for 2012: 12.3 M.

• High value for 2020: 14.1 M.

The linguistic variables for CO_2, CH_4, and N_2O. Emission data are with the Reference of Table 4, Table 5 and Table 6.

Table 4. Linguistic variables for CO_2

City	Low	Medium	High
Ahmedabad	10.5 M	12.3 M	14.1 M
Bangalore	14.2 M	15.8 M	17.8 M
Chandigarh	1.8 M	2.2 M	2.7 M
Chennai	12.5 M	14.5 M	16.1 M
Hyderabad	11.1 M	12.6 M	13.8 M
Jaipur	4.6 M	5.6 M	6.4 M
Kolkata	11.2 M	13.2 M	4.8 M
Mumbai	35.7 M	39.1 M	42.1 M
New Delhi	29.5 M	32.5 M	35.6 M
Pune	9.8 M	11.8 M	13.4 M

Table 5. Linguistic variables for CH_4

City	Low	Medium	High
Ahmedabad	1.5 M	1.9 M	2.2 M
Bangalore	1.8 M	2.2 M	2.5 M
Chandigarh	1.0 M	1.5 M	1.7 M
Chennai	1.5 M	1.9 M	2.2 M
Hyderabad	1.6 M	2.0 M	2.3 M
Jaipur	1.3 M	1.7 M	2.0 M
Kolkata	1.7 M	2.1 M	2.4 M
Mumbai	2.0 M	2.5 M	2.8 M
New Delhi	2.3 M	2.7 M	3.0 M
Pune	1.5 M	2.0 M	2.2 M

Table 6. Linguistic variables for N_2O

City	Low	Medium	High
Ahmedabad	1.0 M	1.5 M	1.9 M
Bangalore	1.2 M	1.6 M	2.1 M
Chandigarh	0.6 M	1.2 M	1.5 M
Chennai	1.0 M	1.4 M	1.9 M
Hyderabad	1.1 M	1.6 M	2.0 M
Jaipur	0.8 M	1.3 M	1.7 M
Kolkata	1.1 M	1.7 M	2.0 M
Mumbai	1.3 M	2.0 M	2.2 M
New Delhi	1.5 M	2.2 M	2.4 M
Pune	0.9 M	1.3 M	1.8 M

3.1 *Evaluating the triangular membership values*

Using the formula,

$$\mu_{Triangular}(x) = \max\left(0,\ \min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b}\right)\right)$$

Evaluation of degree of membership (Jaipur 2014 CO_2 emission) $x = 5.2$ in the triangular fuzzy set defined by $a = 4.6$, $b = 5.6$, and $c = 6.4$ as follows:

$$\frac{x-a}{b-a} = \frac{5.2-4.6}{5.6-4.6} = 0.6$$

$$\frac{c-x}{c-b} = \frac{6.4-5.2}{6.4-5.6} = 0.8$$

$$\min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b}\right) = \min(0.6,\ 0.8) = 0.6$$

$$\mu_{Triangular}(x) = \max(0,\ 0.6) = 0.6$$

Therefore, the degree of membership $x = 5.2$ in the fuzzy set defined by $a = 4.6$, $b = 5.6$, and $c = 6.4$ is 0.6.

Evaluation of degree of membership (Mumbai 2018 CO_2 emission) $x = 40.5$ in the triangular fuzzy set defined by $a = 35.7$, $b = 39.1$, and $c = 42.1$ as follows:

$$\frac{x-a}{b-a} = \frac{40.5-35.7}{39.1-35.7} = 1.4118$$

$$\frac{c-x}{c-b} = \frac{42.1-40.5}{42.1-39.1} = 0.5333$$

$$\min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b}\right) = \min(1.4118,\ 0.5333) = 0.6$$

$$\mu_{Triangular}(x) = \max(0,\ 0.6) = 0.5333$$

As a result, the degree of membership for $x = 40.5$ in the fuzzy set described by $a = 35.7$, $b = 39.1$, and $c = 42.1$ is 0.5333. After analyzing all linguistic factors, the triangle membership values from Figure 4 were shown using Matlab code.

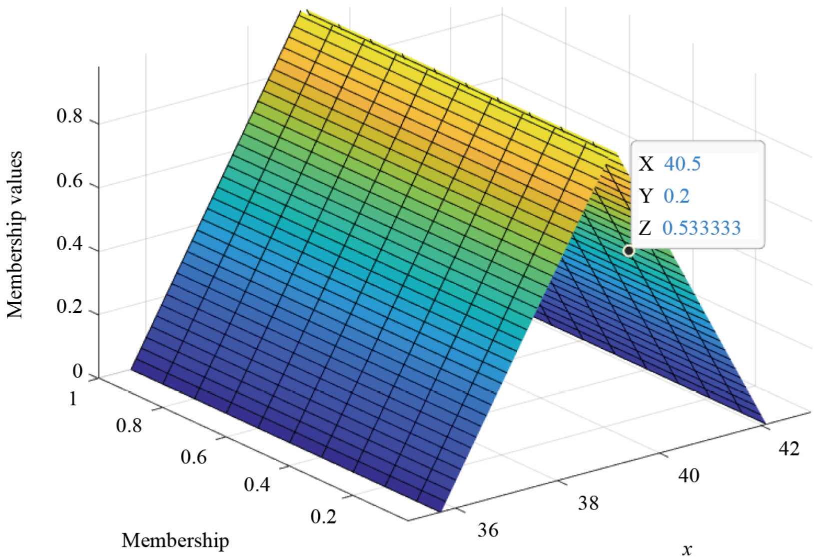

Figure 4. Triangular membership function

Table 7, 8, and 9 shows triangular membership values for raw data from Table 1, 2 and 3.

Table 7. Triangular membership values of CO_2 emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0.2222	0.25	0.2499	0.2	0.2	0.2	0.2	0.1764	0.2	0.1999
2013	0.7777	0.5	0.4999	0.4	0.3999	0.4	0.4	0.3823	0.3999	0.25
2014	0.6666	0.75	0.7499	0.5999	0.6	0.6	0.6	0.5882	0.6	0.5999
2015	0.8888	1	1	0.7999	0.8	0.8	0.6249	0.7941	0.7999	0.7999
2016	0.8888	0.8	0.8	1	1	1	1	1	1	1
2017	0.6666	0.5999	0.6	0.75	0.7499	0.75	0.75	0.7666	0.7741	0.75
2018	0.4444	0.4	0.4	0.5	0.5	0.5	0.5	0.5333	0.5161	0.5
2019	0.2222	0.2	0.2	0.25	0.25	0.25	0.25	0.2666	0.258	0.25
2020	0	0	0	0	0	0	0	0	0	0

Table 8. Triangular membership values of CH_4 emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0	0	0	0	0	0	0	0	0	0
2013	0	0	0	0	0	0	0	0	0	0
2014	0.25	0.2499	0.2	0.25	0.2499	0.2499	0.25	0.2	0.25	0
2015	0.5	0.4999	0.3999	0.5	0.5	0.5	0.4999	0.4	0.5	0.2
2016	0.75	0.7499	0.6	0.75	0.7499	0.75	0.7499	0.5999	0.75	0.6
2017	1	1	0.7999	1	1	1	1	0.7999	1	0.7999
2018	0.6666	0.6666	1	0.6666	0.6666	0.6666	0.6666	1	0.6666	1
2019	0.3333	0.3333	0.4999	0.3333	0.3333	0.3333	0.3333	0.6666	0.3333	0.5
2020	0	0	0	0	0	0	0	0.3333	0	0

Table 9. Triangular membership values of N_2O emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0.2222	0.25	0.2499	0.2	0.2	0.2	0.2	0.1764	0.2	0.1999
2013	0.7777	0.5	0.4999	0.4	0.3999	0.4	0.4	0.3823	0.3999	0.25
2014	0.6666	0.75	0.7499	0.5999	0.6	0.6	0.6	0.5882	0.6	0.5999
2015	0.8888	1	1	0.7999	0.8	0.8	0.6249	0.7941	0.7999	0.7999
2016	0.8888	0.8	0.8	1	1	1	1	1	1	1
2017	0.6666	0.5999	0.6	0.75	0.7499	0.75	0.75	0.7666	0.7741	0.75
2018	0.4444	0.4	0.4	0.5	0.5	0.5	0.5	0.5333	0.5161	0.5
2019	0.2222	0.2	0.2	0.25	0.25	0.25	0.25	0.2666	0.258	0.25
2020	0	0	0	0	0	0	0	0	0	0

3.2 *Linguistic variables for trapezoidal membership values*

1. Low value: The low value reflects the data's lowest range. In this scenario, the low number corresponds to the dataset's minimum value of 10.5 million in 2011. As a result, the low figure for 2011 is 10.5 million.

2. Medium value: The medium value reflects the data's middle range. For example, to determine the middle figure for 2012 the average of emission values for 2011 and 2013. Therefore, the medium value for 2012 is 10.9 M.

3. High value: The high value reflects the data's upper limit. For example, to evaluate the high number for 2019, the average emission values for 2018 and 2020. Therefore, the high value for 2019 is 13.7 M.

4. Very high value: The very high value reflects the data's widest range and that is 14.1 million.

To summarize:

1. Low value for 2011: 10.5 M
2. Medium value for 2012: 10.9 M
3. High value for 2019: 13.7 M
4. Very high value for 2020: 14.1 M

Table 10, 11, and 12 show Linguistic variables for trapezoidal membership values for raw data from Table 1, 2 and 3.

Table 10. Linguistic variables for CO_2

City	Low	Medium	High	Very high
Ahmedabad	10.5 M	11.8 M	13.2 M	14.1 M
Bangalore	14.2 M	15.4 M	16.8 M	17.8 M
Chandigarh	1.8 M	2.0 M	2.4 M	2.7 M
Chennai	12.5 M	13.4 M	15.0 M	16.1 M
Hyderabad	11.1 M	12.0 M	13.5 M	13.8 M
Jaipur	4.6 M	5.1 M	5.8 M	6.4 M
Kolkata	11.2 M	12.8 M	14.0 M	14.8 M
Mumbai	35.7 M	38.1 M	40.3 M	42.1 M
New Delhi	29.5 M	31.0 M	33.0 M	34.8 M
Pune	9.8 M	10.6 M	11.9 M	13.4 M

Table 11. Linguistic variables for CH_4

City	Low	Medium	High	Very high
Ahmedabad	1.3 M	2.0 M	2.2 M	2.2 M
Bangalore	1.6 M	2.3 M	2.5 M	2.5 M
Chandigarh	0.8 M	1.5 M	1.7 M	1.7 M
Chennai	1.3 M	2.0 M	2.2 M	2.2 M
Hyderabad	1.4 M	2.1 M	2.3 M	2.3 M
Jaipur	1.1 M	1.8 M	2.0 M	2.0 M
Kolkata	1.5 M	2.2 M	2.4 M	2.4 M
Mumbai	1.8 M	2.5 M	2.7 M	2.7 M
New Delhi	2.1 M	2.8 M	2.9 M	3.0 M
Pune	1.2 M	1.8 M	2.2 M	2.2 M

Table 12. Linguistic variables for N_2O

City	Low	Medium	High	Very high
Ahmedabad	1.0 M	1.35 M	1.7 M	2.0 M
Bangalore	1.2 M	1.6 M	2.0 M	2.4 M
Chandigarh	0.6 M	0.9 M	1.2 M	1.5 M
Chennai	1.0 M	1.325 M	1.65 M	2.0 M
Hyderabad	1.1 M	1.45 M	1.8 M	2.2 M
Jaipur	0.8 M	1.05 M	1.3 M	1.6 M
Kolkata	1.1 M	1.45 M	1.8 M	2.2 M
Mumbai	1.3 M	1.7 M	2.1 M	2.5 M
New Delhi	1.5 M	1.9 M	2.3 M	2.7 M
Pune	0.9 M	1.15 M	1.4 M	1.7 M

3.3 *Evaluating the membership values using trapezoidal membership function*

- Evaluate the membership degree based on the adjacency of x to a is:

$$\frac{x-a}{b-a} = \frac{14.1-12.5}{13.4-12.5} = 0.7419$$

- Evaluate the membership degree based on the adjacency of x to d is:

$$\frac{d-x}{d-c} = \frac{16.1-14.1}{16.1-15.0} = 1.0$$

- Evaluate the minimum of the membership degree evaluated in steps 1 and 2:

$$\min(0.7419,\ 1.0) = 0.7419$$

- Evaluate the final membership degree by taking the maximum of the result in steps 3 and 0:

$$\max(0,\ 0.7419) = 0.7419$$

For the raw data in Table 10, 11, and 12, Trapezoidal membership values are displayed in Table 13, 14, and 15. Once every linguistic variable has been examined, the Matlab algorithm has been used to display the trapezoidal membership values from Figure 5.

Table 13. Trapezoidal membership values of CO_2 emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0.3076	0.3333	0.4999	0.444	0.2222	0.4	0.25	0.2499	0.4	0.4999
2013	0.6153	0.6666	1	0.8888	0.6666	0.8	5	0.5416	0.7999	1
2014	0.923	1	1	1	1	1	0.75	0.8333	1	1
2015	1	1	1	1	1	1	1	1	1	1
2016	1	1	1	1	1	1	1	1	1	1
2017	1	1	1	1	1	1	1	1	0.8888	0.8
2018	0.8888	0.8	0.6666	0.7272	1	0.6666	1	0.8888	0.4444	0.5333
2019	0.4444	0.4	0.3333	0.3636	1	0.3333	0.5	0.4444	0	0.2666
2020	0	0	0	0	0	0	0	0	0	0

Table 14. Trapezoidal membership values of CH_4 emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0.1111	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1666
2013	0.2222	0.2857	0.2857	0.2857	0.2857	0.2857	0.2857	0.2857	0.2857	0.3333
2014	0.3333	0.4285	0.4285	0.4285	0.4285	0.4285	0.4285	0.4285	0.4285	0.5
2015	0.4444	0.5714	0.5714	0.5714	0.5714	0.5714	0.5714	0.5714	0.5714	0.6666
2016	0.5555	0.7142	0.7142	0.7142	0.7142	0.7142	0.7142	0.7142	0.7142	1
2017	0.6666	0.8571	0.8571	0.8571	0.8571	0.8571	0.8571	0.8571	0.8571	1
2018	0.7777	1	1	1	1	1	1	1	1	1
2019	0.8888	1	1	1	1	1	1	1	1	1
2020	0	0	0	0	0	0	0	0	0	0

Table 15. Trapezoidal membership values of N_2O emission

Year/City	Ahmedabad	Bangalore	Chandigarh	Chennai	Hyderabad	Jaipur	Kolkata	Mumbai	New Delhi	Pune
2011	0	0	0	0	0	0	0	0	0	0
2012	0.2857	0.25	0.3333	0.3076	0.2857	0.3999	0.2857	0.2499	0.25	0.4
2013	0.5714	0.4999	0.6666	0.6153	0.5714	0.7999	0.5714	0.5	0.5	0.8
2014	0.8571	0.7499	1	0.923	0.8571	1	0.8571	0.75	0.75	1
2015	1	1	1	1	1	1	1	1	1	1
2016	1	1	1	1	1	1	1	1	1	1
2017	1	1	1	1	1	0.6666	1	1	1	0.6666
2018	1	1	0.6666	0.8571	1	0.3333	1	1	1	0.3333
2019	0.6666	1	0.3333	0.5714	0.75	0	0.75	1	1	0
2020	0.3333	0.7499	0	0.2857	0.5	0	0.5	0.7499	0.75	0

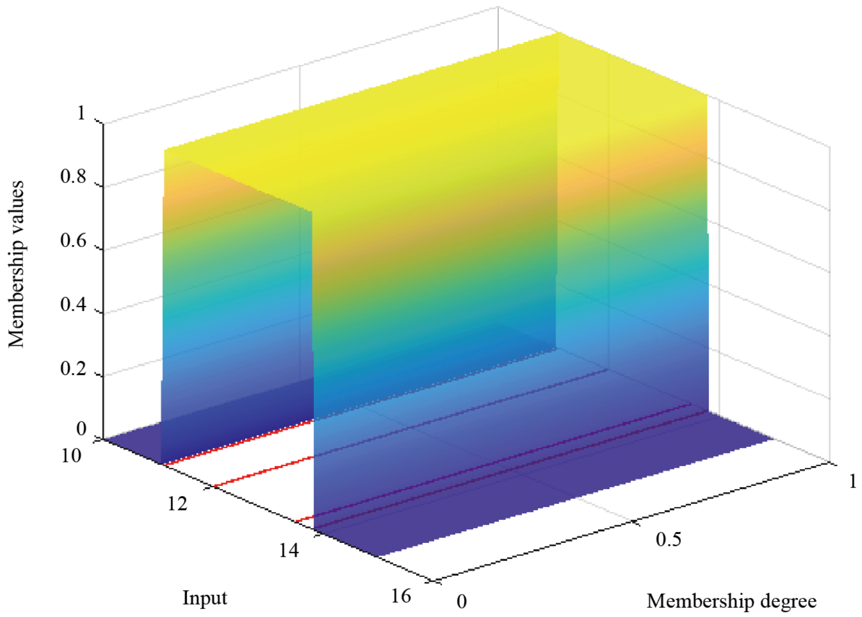

Figure 5. Trapezoidal membership function

4. RMSE calculation

To evaluate the RMSE values for the membership values from Table 16 to 21 for each emission of triangular and trapezoidal membership values:

$$RMSE = \sqrt{\text{AVERAGE}\left((\text{P\_range} - \text{A\_range})^2\right)}$$

Table 16. RMSE of triangular membership values

CO_2 emission	
Cities	RMSE
Ahmedabad	0.8516764239
Bangalore	0.9506892252
Chandigarh	0.6604020669
Chennai	0.8779409838
Hyderabad	0.9046569991
Jaipur	0.9175622306
Kolkata	0.9046569991
Mumbai	1.048237569
New Delhi	1.244487846
Pune	0.9989536751

Table 17. RMSE of triangular membership values

CH_4 emission	
Cities	RMSE
Ahmedabad	1.442712184
Bangalore	1.735371559
Chandigarh	0.9539654098
Chennai	1.442712184
Hyderabad	1.539958586
Jaipur	1.249574906
Kolkata	1.637521129
Mumbai	1.863865995
New Delhi	2.227427764
Pune	1.426541973

Table 18. RMSE of triangular membership values

N_2O emission	
Cities	RMSE
Ahmedabad	0.9447624061
Bangalore	1.28580053
Chandigarh	0.7094824416
Chennai	1.096627559
Hyderabad	1.17582652
Jaipur	0.9014216572
Kolkata	1.163362943
Mumbai	1.343794203
New Delhi	1.538114059
Pune	1.006254442

Table 19. RMSE of trapezoidal membership values

CO_2 emission	
Cities	RMSE
Ahmedabad	11.74046122
Bangalore	15.42629276
Chandigarh	1.681950191
Chennai	13.7134295
Hyderabad	11.79100983
Jaipur	4.931362129
Kolkata	12.21341476
Mumbai	38.2477652
New Delhi	31.87459477
Pune	11.06506514

Table 20. RMSE of trapezoidal membership values

CH_4 emission	
Cities	RMSE
Ahmedabad	1.379716451
Bangalore	1.58455068
Chandigarh	0.8189950299
Chennai	1.29258766
Hyderabad	1.389528287
Jaipur	1.100350335
Kolkata	1.486874191
Mumbai	1.78067764
New Delhi	2.076254045
Pune	1.193049874

Table 21. RMSE of trapezoidal membership values

N_2O emission	
Cities	RMSE
Ahmedabad	0.8516764239
Bangalore	0.9506892252
Chandigarh	0.6604020669
Chennai	0.8779409838
Hyderabad	0.9046569991
Jaipur	0.9175622306
Kolkata	0.904656999
Mumbai	1.048237569
New Delhi	1.244487846
Pune	0.9989536751

Comparing the mean RMSE values for each membership function in terms of error percentage.

$$\text{M.RMSE(Tri)} = \frac{(RMSE1 + 2 + \ \dots \ + 10)}{10}$$

$$\text{M.RMSE(Tra)} = \frac{(RMSE1 + 2 + \ \dots \ + 10)}{10}$$

Evaluating the error percentage for each membership function:

$$Er.P = \left(\frac{((\text{M RMSE(Tra)} - \text{M RMSE (Tri)})}{\text{M RMSE (Tra)}} \right) \times 100$$

The error percentage represents the error difference between the two membership functions from Table 22. If the error percentage is positive, the trapezoidal membership function is more accurate than the triangular membership function, and vice versa.

Table 22. Average of the RMSE values

Membership function	Average
Triangular Membership value for CO_2	15.4664
Triangular Membership value for CH_4	1.552
Triangular Membership value for N_2O	1.1165
Trapezoidal Membership value for CO_2	15.2685
Trapezoidal Membership value for CH_4	1.4103
Trapezoidal Membership value for N_2O	0.9359

Substituting the RMSE mean values of triangular and trapezoidal membership values of CO_2 emission

$$Er.P = \left(\frac{15.2685 - 15.4665}{15.2685}\right) \times 100$$

$$Er.P = \left(\frac{-0.198}{15.2685}\right) \times 100$$

$$Error\ Percentage \approx -1.2944\%$$

Substituting the RMSE mean values of triangular and trapezoidal membership values of CH_4 eemission

$$Er.P = \left(\frac{1.4163 - 1.5520}{1.4163}\right) \times 100$$

$$Er.P = \left(\frac{0.1357}{1.4163}\right) \times 100$$

$$Error\ Percentage \approx 8.74\%$$

Substituting the RMSE mean values of triangular and trapezoidal membership values of N_2O emission

$$Er.P = \left(\frac{0.9359 - 1.1165}{0.9359}\right) \times 100$$

$$Er.P = \left(\frac{-0.1806}{1.1165}\right) \times 100$$

$$Error\ Percentage \approx -19.32\%$$

Figure 6, 7, and 8 show a comparison of all RMSE mean values.

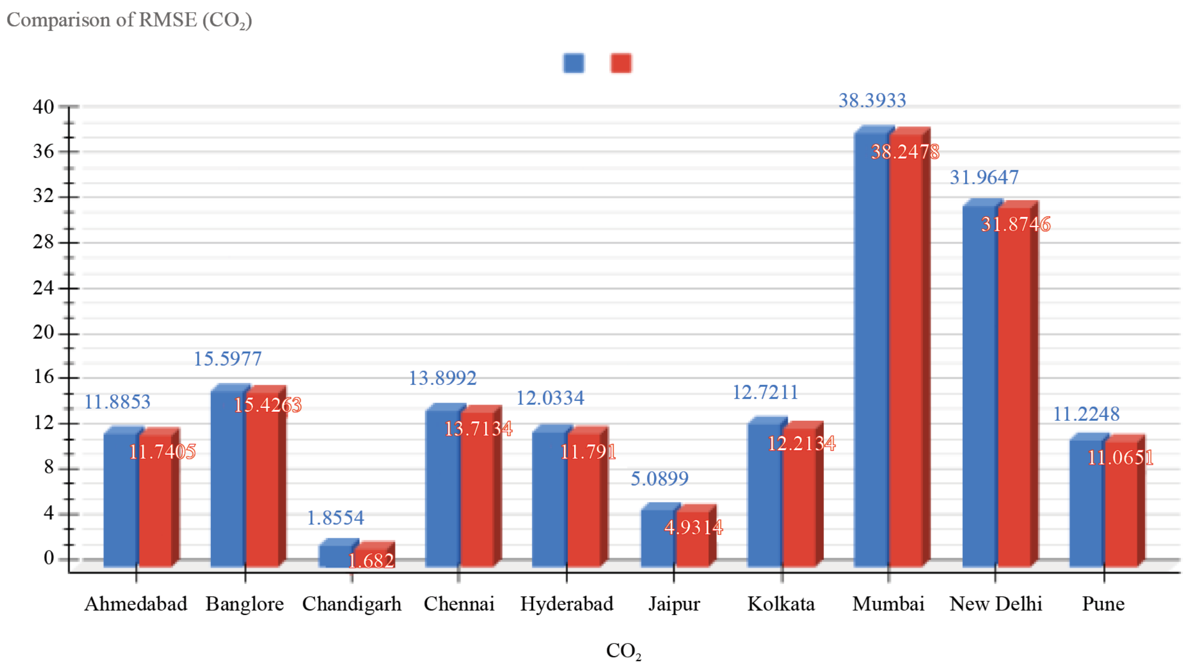

Figure 6. Comparison of RMSE mean values for the membership functions for CO_2

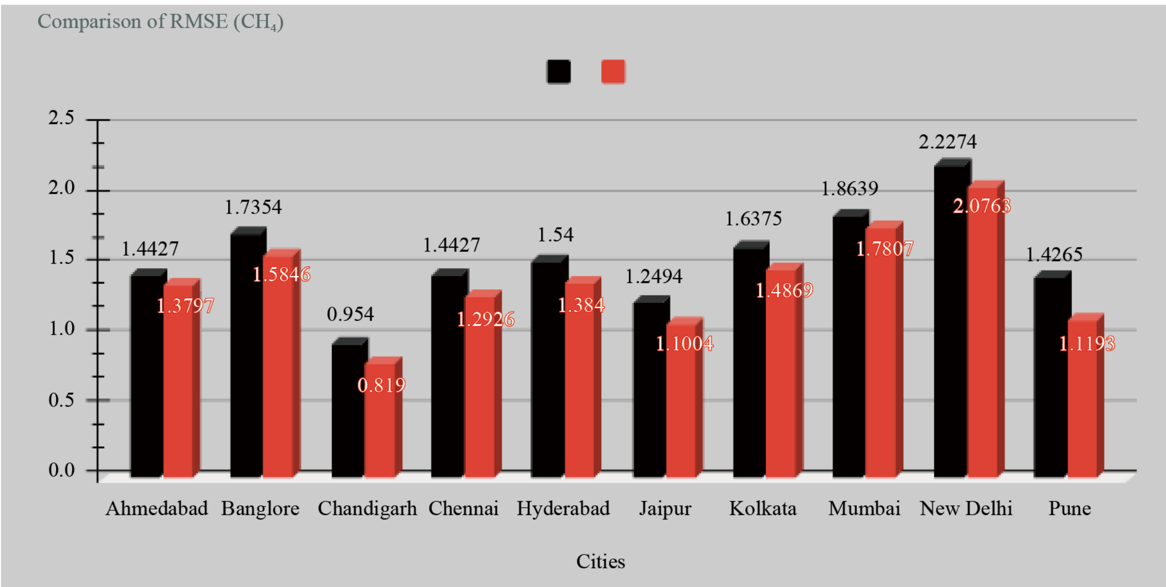

Figure 7. Comparison of RMSE mean values for the membership functions for CH_4

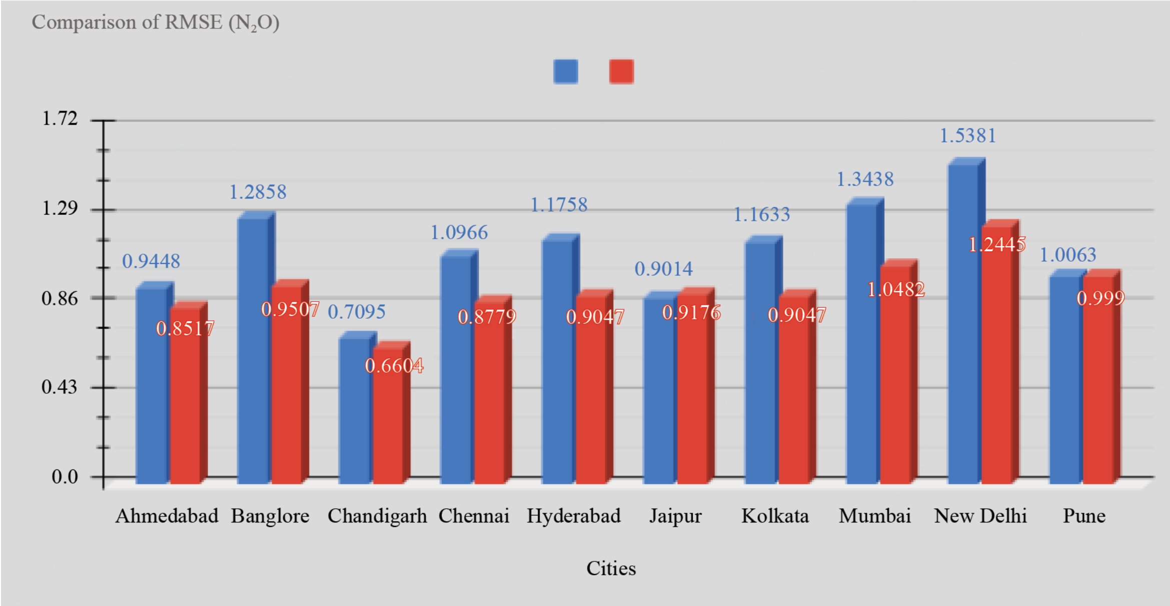

Figure 8. Comparison of RMSE mean values for the membership functions for N_2O

5. Remark

In this study evaluated the performance of the membership functions using RMSE values and percentage error analysis. Initially the results indicated with sigmoid membership function but the results indicated that the trapezoidal membership function provided more accurate results for CO_2 and CH_4 emissions, while the triangular membership function was more accurate for N_2O emissions. These findings highlight the importance of selecting appropriate membership functions tailored to specific gases to enhance emission forecast accuracy. The study emphasizes the significance of such insights for decision-makers, urban planners, and environmental agencies involved in emissions reduction measures and smart city development.

6. Conclusion

The project examined CO_2, N_2O, and CH_4 emissions in smart cities in India over 10 years. The study used triangular and trapezoidal membership functions to determine the emission data's membership values. Furthermore, the root mean square error (RMSE) values and percentage errors for each emission kind were computed as follows: CO_2 is -1.2944%, CH_4 is 8.74%, and N_2O is -19.32%. Based on the results, it is possible to conclude that the performance of the membership functions differs depending on the emission type under consideration. Let's look at each emission separately to see how successful the membership functions are. Starting with CO_2 emissions, the -1.2944% percentage error indicates that the triangle membership function beats the trapezoidal membership function. This means that the triangle membership function estimates CO_2 emissions more accurately in the chosen intelligent cities in India. In terms of CH_4 emissions, the percentage error of 8.74% shows that the trapezoidal membership function outperforms the triangle membership function. As a result, the trapezoidal membership function is more accurate in estimating CH_4 emissions in a particular environment. Finally, when it comes to N_2O emissions, the percentage error of -19.32% indicates that the triangular membership function outperforms the trapezoidal membership function. As a result, when it comes to N_2O emissions in India's smart cities, the triangular membership function produces more accurate estimates. In conclusion, the performance of the membership functions for emissions prediction in India's smart cities differs based on the individual gas being analyzed. The triangle membership function is more accurate for N_2O emissions, but the trapezoidal membership function is more accurate for CH_4 emissions. However, for predicting CO_2 emissions in the present situation, the triangle membership function outperforms.

For the future aspects, When analyzing emissions data, these findings emphasize the significance of adapting membership functions to specific gases. Policymakers, urban planners, and environmental agencies may make more informed decisions to successfully reduce and control emissions in smart cities by selecting the proper membership function. It is far-reaching to note that the findings reached in this research are based on the unique dataset and approach employed. It is advised that more research and analysis be conducted to corroborate these findings and investigate additional aspects that may impact the efficacy of membership functions in emission prediction in smart cities.

Finally, the study sheds light on the efficacy of triangular and trapezoidal membership functions in predicting CO_2, CH_4, and N_2O emissions in India's smart cities. When the percentage of mistakes is considered, it is clear that the choice of the membership function is critical in properly projecting emissions. The findings contribute to ongoing efforts to create sustainable and ecologically friendly cities, as well as to facilitate informed decision-making and build a greener future.

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Data availability

In order to make our conclusions for this study, the authors did not use any scientific data.

Conflict of interest

There is no conflict of interest among the authors.

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