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A Distinctive Symmetric Analyzation of Improving Air Quality Using Multi-Criteria Decision Making Method under Uncertainty Conditions

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Abstract: This world has a wide range of technologies and possibilities that are available to control air pollution. Still, finding the best solution to control the contamination of the air without having any impact on humans is a complicated task. This proposal helps to improve the air quality using the multi-criteria decision making method. The decision to improve air quality is a challenging problem with today's technology and environmental development level. The multi-criteria decision making method is quite often faced with conditions of uncertainty, which can be tackled by employing fuzzy set theory. In this paper, based on an objective weighting method (CCSD), we explore the improved fuzzy MULTIMOORA approach. We use the classical Interval-Valued Triangular Fuzzy Numbers (IVTFNs), viz. the symmetric lower and upper triangular numbers, as the basis. The triangular fuzzy number is identified by the triplets; the lowest, the most promising, and the highest possible values, symmetric with respect to the most promising value. When the lower and upper membership functions are equated to one, we get the normalized interval-valued triangular fuzzy numbers, which consist of symmetric intervals. We evaluate five alternatives among the four criteria using an improved MULTIMOORA method and select the best method for improving air quality in Tamil Nadu, India. Finally, a numerical example is illustrated to show the efficiency of the proposed method.

Keywords: MCDM; air quality improvement; air pollution; fuzzy MULTIMOORA; decision making; symmetric

1. Introduction

The environment, of which we are a part, consists of living species, weather, climate, and natural resources. A healthy co-existence of all the various factors of the environment makes this existence a pro-existence. In reality, life on Earth is far from being in equilibrium with this existence, rather facing several environmental issues. Environmental contamination in the form of solid, liquid, or gaseous substances has catastrophic effects on the lives of human beings, flora, and fauna. Environmental contamination leads to the loss of habitats and organisms on the land and in the waters. The foremost causal factors of environmental contamination are pollution and poisoning. Our attention in this paper is on the issue of pollution as it is the single most important environmental issue the modern world faces. Pollution is defined as the presence of impurities or harmful substances at concentration levels that are beyond acceptable levels. When it is exposed too much to these pollutants, the quality of life in this environment is compromised. Pollution is associated with the quality of the air, the water, the soil, the sea, noise, etc.

One of the most devastating types of pollution is that of air pollution. As the atmosphere is common to the entire world, the air pollution in the troposphere and in the stratosphere affects the entire living beings on earth. Air pollution comes in the form of solid, liquid, or gaseous substances, such as the contamination of gases, dust, smoke, fumes, chemical particulates, and biological materials in the atmosphere that are undesirable and injurious to human beings, animals, and plants. Contamination of the air has become a matter of serious concern in many parts of the world. In India, the urban areas are the most polluted. The reasons behind the air pollution are industrialization, vehicle emissions, deforestation, population growth, etc. Humans alone cannot be blamed for all of this type of contamination. Nature has its part in this as well. Pollution of air can derive from human actions, as well as natural processes. Natural process that pollute the air include forest fires, wind erosion, and volcanic eruptions. Some of the major pollutants produced by human activity include carbon oxides (CO and CO_2), lead (Pb), nitrogen oxides (NO and NO_2), ozone (O_3), Particulate Matter (PM), and Sulphur dioxide (SO_2).

Particulate matter (PM) arises from the burning of fossil fuels, such as by vehicles, at construction sites, and by power plants. Carbon oxides are created by the incomplete combustion of fuel by vehicles and from industrial production. Nitrogen oxides come from coal-burning power plants, manufacturing processes, and electrical energy utilities. Sulphur dioxide originates from power-producing plants and fossil fuel combustion, and it reacts with oxygen and water vapour, forming acid rain after combining with atmospheric water. Ozone comes from oxides of nitrogen and Volatile Organic Compounds from automobile emissions, electric utilities, and industrial companies, as well as ultraviolet rays from the Sun. Lead arises from incineration, metal dispensation, and fossil fuel combustion. These substances may be absorbed in the air, which can have detrimental health, economic, or aesthetic effects. The nomenclature with their acronyms or abbreviations used in this research paper are given in Table 1.

Table 1. Nomenclature.

DM	Decision Making
NDM	Normalized Decision Matrix
MCDM	Multi-Criteria Decision Making
MULTIMOORA	Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form
CCSD	Correlation Coefficient and Standard Deviation
SWARA	Step Wise Weight Assessment Ratio Analysis
SAW	Simple Additive Weighting
VIKOR	VIsekriterijumsko KOmpromisno Rangiranje
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
AHP	Analytic Hierarchy Process
IVIFS	Interval-Valued Intuitionistic Fuzzy Sets
IVTFN	Interval-Valued Triangular Fuzzy Number
NIVTFN	Normalized Interval-Valued Triangular Fuzzy Number
CEVs	Clean Energy Vehicles
RS	Ratio System
RP	Reference Point
FMF	Full Multiplicative Form

2. Literature Review

In this section, we review some studies related to Multi-Criteria Decision Making (MCDM), air pollution and improving air quality systems. Several studies are provided the reasons for air pollution. It is highly beneficial if the sources for improving the air quality in Tamil Nadu, India were addressed. Vlachokostaset al. [1] discussed the most polluted cities in Europe, particularly concerning airborne particle pollutants in those cities and natural gas saturation in buildings and metro constructions. Jai Prakash et al. [2] presented the comparison between 2005-model diesel cars and 2010-model diesel cars to prove how the Carbon Monoxide emissions in Delhi were decreased and discussed the other emission factors of Carbon oxides and Nitrogen oxides. This paper provides the age and maintenance of vehicles as the important factors for reducing emissions. Jaiprakash et al. [3] show the chemical and $PM_{2.5}$ emission factors emitted from light vehicles in Delhi for reducing the pollution by using alternative fuels. In the year 2016, Kamal Jyoti Maji et al. [4] analyzed the $PM_{2.5}$-related health effects in 338 cities in China. Irwin M. Hutten [5] proposed air filter applications to control air pollution. Shiva Nagendra et al. [6] presented the Chennai city air quality monitoring system, the results indicated that the $PM_{2.5}$ absorption was the highest in busy traffic sites, and the higher concentrations of CO_2, NO_2, and O_3 were observed while traveling by bus in the morning, evening and afternoon. This result was obtained from different days in a week. Guoliang et al. [7] assessed the different air filtration technologies taking into account factors such as air quality improvement, filtration performance energy, and their economic behavior, thermal comfort, and sound impact. Chengjiang Li et al. [8] suggested that the Chinese government has to promote clean energy vehicles, that can be provided by methanol, or ethanol, electricity, and gas. Decision-maker has selected the best Clean Energy Vehicles (CEVs) using the Analytic Hierarchy Process (AHP) and the VIsekriterijumsko KOmpromisno Rangiranje (VIKOR) method. Here, four categories of clean energy vehicles are preferred by thirty-five experts, including electric, gas, methanol, and ethanol vehicles. It is found out that the electric vehicles have the highest ranking compared to other vehicles. If the air pollution level is less than the least level of health loss in India, the life expectancy in each state is determined and the number of deaths and disabilities in India shown from India State-Level Disease Burden Initiative Air Pollution Collaborators is calculated [9]. Then the annual population-weighted mean of $PM_{2.5}$ in India of the year 2017 was calculated and then sustainably improving the planning and implementation of air pollution control efforts across India was achieved. Michael Brauer et al. [10] discussed the highest disease burdens caused by air pollution in India because of population growth, which increases the $PM_{2.5}$ emissions. Yaparla Deepthi et al. [11] present the measuring of PM concentrations in rural households using different fuels and kitchens type fuels and also reduce the PM levels and health risks. The level of $PM_{2.5}$, PM_{10} and trace metals with $PM_{2.5}$ comes from cooking with fuel-wood. This result shows that aboriginal women who cook with wood are at increased risk of developing cancer [12]. Air pollution knowledge assessments city programs commodity analyzed 20 Indian cities that are in urban emission inventories and estimated the annual emissions. The study helps the policymakers to implement the baselines to improve air quality for long term in these cities [13]. This study deals with reducing the ambient fine particulate matter emitted from the process involved in generation of power, industries, and transportation in India using the current laws and alternative policy scenarios based on simulations with the GAINS integrated assessment model [14]. Sarath et al. [15] presented the state of air quality in emissions inventory in Bengaluru for the pollutants necessary for the chemical transport model. Jingzheng Ren et al. [16] show the best alternative fuel for marine navigation using fuzzy group MCDM method. They have been proposed by combining fuzzy logarithmic least squares and fuzzy Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method. Parvin Moridi et al. [17] proposed to choose the optimal technologies for filtering the air in petrochemical industries using a MCDM method based on a fuzzy TOPSIS model.

From the above discussion and motivation, there is a need to fill the research gap for air quality improvement methods in Tamil Nadu, India. Hence, we put in place the improved fuzzy Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA) method. In our work, we use the main criteria of environment, economic, technology, and social aspects to find the best method for improving air quality in Tamil Nadu, India. The decision making (DM) is the action for selecting the finest alternative based on a set of criteria. Many researchers have developed a host of methods based on MCDM to overcome the problems and to simplify the DM process. By employing the MCDM methods, the decision-making process is enhanced with proficiency, logic, and clarity. Through the enhancement of proficiency, the system is highly rewarded. By employing a better logic, the process is exonerated from from its indecisiveness. Finally, by improving the clarity, the decision-making process has a better appeal even for the amateurs in the field. These three impacts in the decision-making process are achieved nearly through the quintessential MCDM. The MULTIMOORA is one among the most practical MCDM models, which is used in various types of research to solve complex DM problems and it is derived from the Multi-Objective Optimization by Ratio Analysis (MOORA) model. The MOORA model consists of two approaches, viz., the Ratio System approach and Reference Point approach, that are introduced by Brauers and Zavadskas [18]. Topping the MOORA with a full multiplicative form was done first in [19]. This in due course improved the strength of the MOORA. Owing to this, the MOORA model is much sought-after by decision scientists and practitioners. Many researchers use it to solve complicated decision-making problems [20–25]. Improving air quality and modeling emissions reduction scenarios were discussed by J. Monjardino et al [26]. Some developments of this method of research also are discussed here.

Casanovas-Rubio et al. [27] developed a method for assessing the sustainability of trenches based on the MIVES decision-making method. Chao Song et al. [28] explore the structure of Quality Function Deployment (QFD) using linguistic Z-numbers (LZNs) and integrate the weights of expert team members and customer needs. Here, Step Wise Weight Assessment Ratio Analysis (SWARA) and Standard Deviation (SD) methods are presented to get the subjective and objective weights of customer needs. The SWARA method is a newly established method for weighting which has been used by Jalil Heidary Dahooie et al. [29]. Arian Hafezalkotob et al. [21] provided an overview of MULTIMOORA by classifying and examing key research theoretically and practically. Shui-Xia Sen et al. [30] have proposed an extended probability linguistic MULTIMOORA and Choquet integral operator for obtaining the class of cloud-based enterprise resource planning (ERP) system. S. Narayanamoorthy et al. [31] evaluated the selection of industrial robots using MCDM models. Baleentis et al. [32] suggested selecting the best candidate to fill the vacancy in a company with the help of fuzzy MULTIMOORA under group decision-making problem. Bringing in fuzzy numbers with the MULTIMOORA was an innovative experiment. Brauers et al. [33] took up this challenge and achieved a convincing mark. Baleentis et al. [34] has found the personnel selection in the field of human resource management using the MULTIMOORA with IVFNs. Hafez Al Kotob et al. [35] proposed the material selection problem using the MULTIMOORA with interval fuzzy numbers. Ru-Xin Nie et al. [36] presented a selection mechanism that can optimize a three-cycle decision-making selection with intuitionistic trapezoidal fuzzy numbers (ITrFPRs). As the practice of clubbing various types of fuzzy numbers with the MULTIMOORA method became prominent, Stanujkic et al. [37] had attempted to use IVTFNs. It is also convincing to see that the neutrosophic set could be connected to the extended the MULTIMOORA method (See Stanujkic et al. [38]). Zavadskas et al. [39] presented the uncertainty problems under the group decision-making method using the extended MULTIMOORA method with IVIFS. Geetha et al. [40] evaluated the health-care waste treatment using intuitionistic hesitant fuzzy MULTIMOORA method, which gives the best solution for that problem. P. Pujadas et al. [41] proposed a new MIVES system clubbed with multi criteria decision making methods. Hong-gang Peng et al. [42] addresses uncertain Z-number information, and also introduced the concept of Z trapezium-normal clouds (ZTNCs). Heidary Dahooie et al. [43] discussed the technological forecasting method selection based on improved fuzzy MULTIMOORA and Correlation Coefficient and Standard Deviation (CCSD) method for finding the best alternative.

The ratio system (RS), the reference point (RP), and the full multiplicative form (FMF) are three approaches in the fuzzy MULTIMOORA model. The method proposed here is to evaluate various types of alternatives, their scores and their impact. The scores are used to to rank the alternatives individually taking each approach into consideration. The dominance rules are carefully applied to chart out the final ranking. Further, we impose restrictions on the estimation. The restriction is applied by keeping the significance level constant. This is in contrast with the usual consideration of the differences in the aggregation. The final ranking is based upon every alternative data emerged out of the triple alternatives. The CCSD objective weighting model is also used to improve the accuracy and efficiency of the fuzzy MULTIMOORA. As initially proposed and substantiated by Wang and Luo [44], the CCSD model helps to found the weight of each of the criteria in the MCDM. Table 2 provides the data of various countries/city that has improved its air quality using the different types of changes in those urban areas. Here, the present study developed the fuzzy MULTIMOORA with CCSD objective weighting method is aimed at improving the air quality in Tamil Nadu, India with different kind of alternatives and solve the problem of a great way to improving air quality. We have compared our proposed method with TOPSIS and VIKOR methods. We have also conducted the sensitivity analysis.

Table 2. A brief study of air pollution and improving air quality systems around the world.

Authors	Study	City/Country
Hanwei Liang et al. [45]	Alternative fuel-based vehicles for sustainable transportation	China
Kaiyu Chen et al. [46]	Different control strategies have been discussed to reduce air pollution	India
Z. Chalabi et al. [47]	Evaluating air quality policies	UK
Qingyong Wang et al. [48]	An evaluation of multiple factors of air pollutants and economic development	China
Ashwin Sabapathy [49]	Discusses the various fuel quality and vehicular technology improvements	Bangalore
Katerina et al. [50]	the Greek road transport sector using alternative technologies and fuels	Greek
Pei Li et al. [51]	Effects of fuel quality on air pollution	China
Sunil Gulia et al. [52]	Discuss the urban local air quality management framework	India
Gabriel Năstase et al. [53]	Analyzed air pollution and improve the air quality	Romania
Ch. Vlachokostas et al. [1]	Managing urban air pollution and control options	Thessaloniki
Michaela Kendall et al. [54]	New energy vehicle policies	China

3. Motivation and Contributions

3.1. Motivation of the Study

The main of this research study is to select sources that will reduce air pollution and improve air quality. Some hesitations may arise when you study sources that improve air quality because many of them are simple methods that use simple methods to maintain and improve air quality. Many reflective and ambiguous ambitions can arise when considering decisions about their use. Some of the motivations are given below.

- To find an appropriate mathematical model for improving air quality as sources and selecting the best application under the improved fuzzy MULTIMOORA model.
- To overcome these difficult situation we have used IVTFN for MCDM model.

In this research, we find the best way to improve air quality in Tamil Nadu, India using key criteria of environmental, economic, technological, and social aspects. Here, we choose five alternative ways to improve air quality based on the above criteria. Those methods reduce emissions from vehicles, factories, and homes. Therefore, we proposed an improved fuzzy MULTIMOORA model to improve air quality in Tamil Nadu, India.

3.2. Contribution of the Study

The contributions of this research paper are as follows:

- We present the MCDM system, which selects three models, two for the weight detection technique and another for deploying alternatives. They are SWARA, CCSD, and fuzzy MULTIMOORA model, respectively.
- We present the SWARA model to obtain the initial weights of the criteria. The SWARA can overcome the drawbacks of MCDM models in obtaining the initial weight (note that the weights obtained are provided by experts).
- We propose the CCSD objective weighting method with the fuzzy MULTIMOORA method for higher efficiency as compared to other MCDM methods.
- We examine and assess the above application for improving air quality in terms of environmental risk, economic, social aspects, health risk, and technical support. Here, we have selected one of

the most effective applications for improving air quality in Tamil Nadu, India with the help of MCDM models using IVTF numbers.

4. Proposed Method

4.1. Concepts and Definitions

We now describe the fuzzy concepts, the linguistic variables, the interval-valued triangular fuzzy number (IVTFN), and some arithmetic operations.

Definition 1 ([55]). *Let U be a non-empty set. A fuzzy set $\tilde{A}$ in U is characterized by its membership function $\delta_{\tilde{A}} = U \to [0,1]$ and $\delta_{\tilde{A}}(U)$ is interpreted as the degree of membership of element u in fuzzy set $\tilde{A}$ for each $u \in U$. That is,*

$$\tilde{A} = \{(u, \delta_{\tilde{A}}(u))|u \in U\}. \tag{1}$$

The triangular fuzzy number is characterized by a triplet of real numbers (l, m, u), where l represents the lowest possible value, m represents the most promising value and u represents the highest possible value (Dubois Prade 1980) [56], Berry (1992) [57], Kahraman et al. (2004) [58]). These triplets are symmetric with respect the mid-value, i.e., the most promising value, m.

Definition 2 ([59]). *An interval-valued triangular fuzzy number (IVTFN) (Yao and Lin [59]) and its graphical representation is given with Figure 1.*

$$\tilde{T} = [\tilde{T}^L, \tilde{T}^U] = [(t'_l, t'_m, t'_u; \omega'_T), (t_l, t_m, t_u; \omega_T)] \tag{2}$$

where $\tilde{T}^L$ and $\tilde{T}^U$ denote the lower and upper triangular fuzzy numbers, $\tilde{T}^L \subset \tilde{T}^U$. The l', m', and u' describe a $\tilde{T}^L$ and l, m, and u describe a $\tilde{T}^U$ and $\mu_{\tilde{T}}(x)$ as their membership functions. The lower membership function is $\omega'_T = \mu_{\tilde{T}^L}(x)$ and $\omega_T = \mu_{\tilde{T}^U}(x)$ is the upper membership function. There are three intervals that are used here, viz., $(l', l), (m', m)$ and (u', u). As indicated in Figure 1, these intervals represent a symmetric system.

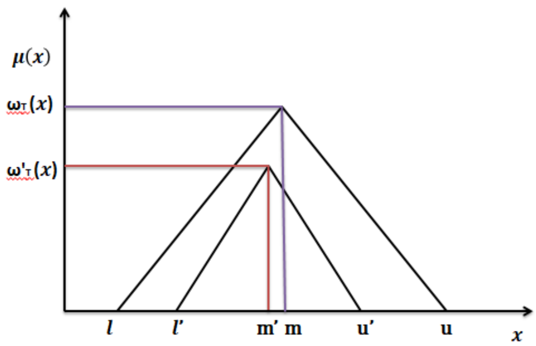

Figure 1. Interval-valued triangular fuzzy numbers (IVTFN).

The two IVTFNs are $\tilde{P} = [\tilde{P}^L, \tilde{P}^U]$ and $\tilde{Q} = [\tilde{Q}^L, \tilde{Q}^U]$. The arithmetic operations can be expressed as Equations (3)–(6)

$$\begin{aligned}\tilde{P} + \tilde{Q} = [&(p'_l + q'_l, p'_m + q'_m, p'_u + q'_u; min(\omega'_P, \omega'_Q)),\\ &(p_l + q_l, p_m + q_m, p_u + q_u; min(\omega_P, \omega_Q))]\end{aligned} \tag{3}$$

$$\begin{aligned}\tilde{P} - \tilde{Q} = [&(p'_l - q'_u, p'_m - q'_m, p'_u - q'_l; min(\omega'_P, \omega'_Q)),\\ &(p_l - q_u, p_m - q_m, p_u - q_l; min(\omega_P, \omega_Q))]\end{aligned} \tag{4}$$

$$\tilde{P} \times \tilde{Q} = [(p'_l \times q'_l, p'_m \times q'_m, p'_u \times q'_u; min(\omega'_P, \omega'_Q)), (p_l \times q_l, p_m \times q_m, p_u \times q_u; min(\omega_P, \omega_Q))] \quad (5)$$

$$\tilde{P} \div \tilde{Q} = [(p'_l \div q'_u, p'_m \div q'_m, p'_u \div q'_l; min(\omega'_P, \omega'_Q)), (p_l \div q_u, p_m \div q_m, p_u \div q_l; min(\omega_P, \omega_Q))] \quad (6)$$

Definition 3. *A particular case of the IVTFN is the normalized IVTFN, $\omega'_T = \omega_T = 1$ with the same mode, which is represented in Equation (7) and Figure 2 shows a graphical representation of NIVTFN that is highly symmetric.*

$$\tilde{T} = [\tilde{T}^l, \tilde{T}^u] = [(l, l'), m, (u', u)] \quad (7)$$

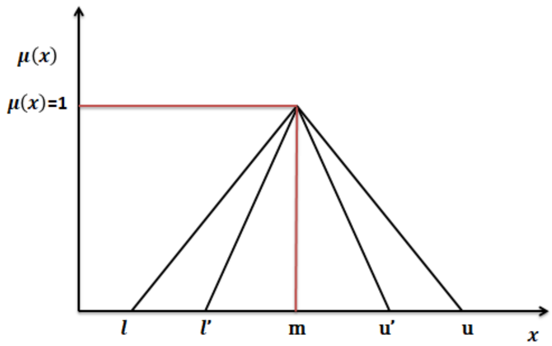

Figure 2. Normalized Interval-valued triangular fuzzy number (NIVTFN).

The basic operations of the NIVTFNs are:

The two NIVTFNs with the same mode are $\tilde{P} = [(p_l, p'_l), p_m, (p'_u, p_u)]$ and $\tilde{Q} = [(q_l, q'_l), q_m, (q'_u, q_u)]$. Then, the arithmetic operations can be expressed as Equations (8)–(13)

$$\tilde{P} + \tilde{Q} = [(p_l + q_l, p'_l + b'_l), p_m + q_m, (p'_u + q'_u, p_u + q_u)] \quad (8)$$

$$\tilde{P} - \tilde{Q} = [(p_l - q_u, p'_l - b'_u), p_m - q_m, (p'_u - q'_l, p_u - q_l)] \quad (9)$$

$$\tilde{P} \times \tilde{Q} = [(p_l \times q_l, p'_l \times b'_l), p_m \times q_m, (p'_u \times q'_u, p_u \times q_u)] \quad (10)$$

$$\tilde{P} \div \tilde{Q} = [(p_l \div q_u, p'_l \div b'_u), p_m \div q_m, (p'_u \div q'_l, p_u \div q_l)] \quad (11)$$

$$\lambda \times \tilde{P} = [(\lambda \times p_l, \lambda \times p'_l), \lambda \times p_m, (\lambda \times p'_u, \lambda \times p_u)] \quad (12)$$

$$\frac{\tilde{P}}{\lambda} = \left[(\frac{p_l}{\lambda}, \frac{p'_l}{\lambda}), \frac{p_m}{\lambda}, (\frac{p'_u}{\lambda}, \frac{p_u}{\lambda}) \right] \quad (13)$$

Definition 4. *Linguistic variable deals with many real-world decision-making problems which are more complex and uncertain. Many research studies have different linguistic variables with fuzzy numbers (Chen 2000 [60], Mahdavi et al., 2008 [61], Wang et al., 2006 [62]). Here, the linguistic variables with interval-valued triangular fuzzy numbers to evaluate the alternatives are presented in Table 3. These variables represent a balanced and symmetric scale.*

Table 3. Fuzzy linguistic variables.

Fuzzy Number	Linguistic Term
$[(0.0, 0.0), 0.1, (0.2, 0.25)]$	Very Low (VL)
$[(0.15, 0.2), 0.3, (0.4, 0.45)]$	Low (L)
$[(0.35, 0.4), 0.5, (0.6, 0.65)]$	Medium (M)
$[(0.55, 0.6), 0.7, (0.8, 0.85)]$	High (H)
$[(0.75, 0.8), 0.9, (0.9, 0.95)]$	Very High (VH)

4.2. Materials and Mathematical Methods

4.2.1. MULTIMOORA

The MULTIMOORA is one of the most accomplished the MCDM models evolved from the seminal contributions of Brauers and Zavadskas [63]. The MOORA method has two parts, the ratio system and the reference point approach. But, the MULTIMOORA method is more robust than the MOORA method. It has three approaches: ration system (RS), reference point (RP), and full multiplicative form (FMF). The steps of the fuzzy MULTIMOORA method are presented in Figure 3.

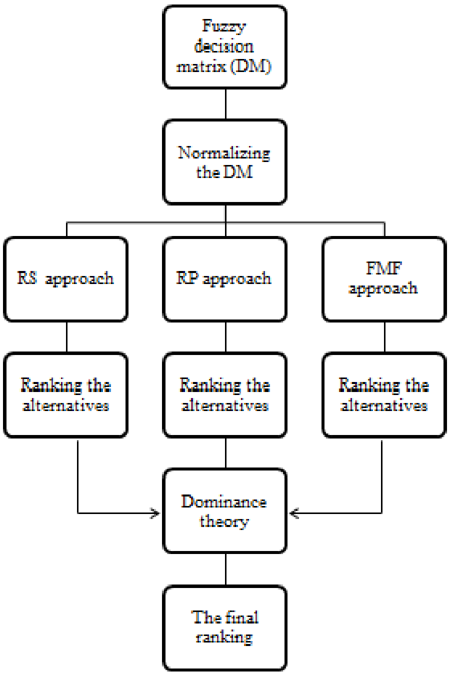

Figure 3. Fuzzy Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA) method.

4.2.2. The Fuzzy Ratio System

The fuzzy RS approach is an important approach in the MULTIMOORA method. There are five steps in the fuzzy RS method [64]. We will address them now.

Step 1: Fuzzy decision matrix formation

We begin creating the A^e decision matrix using IVTFNs according to Table 4. The variables r, v, i and j denote the number of alternatives, the numbers of criteria, the alternative and the criterion, respectively. The measured performance of the ith alternative with respect to the jth criterion is denoted as a_{ij}. The evaluation of the alternatives by the experts is e.

Table 4. Decision matrix A^e.

$[(a_{11}^{(e)l}, a_{11}^{(e)l'}), a_{11}^{(e)m}, (a_{11}^{(e)u'}, a_{11}^{(e)u})]$	$[(a_{12}^{(e)l}, a_{12}^{(e)l'}), a_{12}^{(e)m}, (a_{12}^{(e)u'}, a_{12}^{(e)u})]$	$\dots$	$[(a_{1v}^{(e)l}, a_{1v}^{(e)l'}), a_{1v}^{(e)m}, (a_{1v}^{(e)u'}, a_{1v}^{(e)u})]$
$[(a_{21}^{(e)l}, a_{21}^{(e)l'}), a_{21}^{(e)m}, (a_{21}^{(e)u'}, a_{21}^{(e)u})]$	$[(a_{22}^{(e)l}, a_{22}^{(e)l'}), a_{22}^{(e)m}, (a_{22}^{(e)u'}, a_{22}^{(e)u})]$	$\dots$	$[(a_{2v}^{(e)l}, a_{2v}^{(e)l'}), a_{2v}^{(e)m}, (a_{2v}^{(e)u'}, a_{2v}^{(e)u})]$
$\dots$	$\dots$	$\ddots$	$\dots$
$[(a_{r1}^{(e)l}, a_{r1}^{(e)l'}), a_{r1}^{(e)m}, (a_{r1}^{(e)u'}, a_{r1}^{(e)u})]$	$[(a_{r2}^{(e)l}, a_{r2}^{(e)l'}), a_{r2}^{(e)m}, (a_{r2}^{(e)u'}, a_{r2}^{(e)u})]$	$\dots$	$[(a_{rv}^{(e)l}, a_{rv}^{(e)l'}), a_{rv}^{(e)m}, (a_{rv}^{(e)u'}, a_{rv}^{(e)u})]$

This decision matrices are formulated with each expert and Equation (14) is used to aggregated them. This matrix is denoted by $\tilde{A}$ given in Table 5.

$$\begin{aligned} \tilde{a_{ij}} &= [(\tilde{a_{ij}}^{l}, \tilde{a_{ij}}^{l'}), \tilde{a_{ij}}^{m}, (\tilde{a_{ij}}^{u'}, \tilde{a_{ij}}^{u})] \\ &= \left[\left(\frac{\sum_{n=1}^{e} a_{ij}^{(n)l}}{e}, \frac{\sum_{n=1}^{e} a_{ij}^{(n)l'}}{e} \right), \frac{\sum_{n=1}^{e} a_{ij}^{(n)m}}{e}, \left(\frac{\sum_{n=1}^{e} a_{ij}^{(n)u'}}{e}, \frac{\sum_{n=1}^{e} a_{ij}^{(n)u}}{e} \right) \right] \end{aligned} \tag{14}$$

Table 5. Decision matrix $\tilde{A}$.

$[(a_{11}^{l}, a_{11}^{l'}), a_{11}^{m}, (a_{11}^{u'}, a_{11}^{u})]$	$[(a_{12}^{l}, a_{12}^{l'}), a_{12}^{m}, (a_{12}^{u'}, a_{12}^{u})]$	$\dots$	$[(a_{1v}^{l}, a_{1v}^{l'}), a_{1v}^{m}, (a_{1v}^{u'}, a_{1v}^{u})]$
$[(a_{21}^{l}, a_{21}^{l'}), a_{21}^{m}, (a_{21}^{u'}, a_{21}^{u})]$	$[(a_{22}^{l}, a_{22}^{l'}), a_{22}^{m}, (a_{22}^{u'}, a_{22}^{u})]$	$\dots$	$[(a_{2v}^{l}, a_{2v}^{l'}), a_{2v}^{m}, (a_{2v}^{u'}, a_{2v}^{u})]$
$\dots$	$\dots$	$\ddots$	$\dots$
$[(a_{r1}^{l}, a_{r1}^{l'}), a_{r1}^{m}, (a_{r1}^{u'}, a_{r1}^{u})]$	$[(a_{r2}^{l}, a_{r2}^{l'}), a_{r2}^{m}, (a_{r2}^{u'}, a_{r2}^{u})]$	$\dots$	$[(a_{rv}^{l}, a_{rv}^{l'}), a_{rv}^{m}, (a_{rv}^{u'}, a_{rv}^{u})]$

Step 2: The Normalization of the matrix

The normalizing procedure generates a matrix that provides a greater data comparison ([32]). The normalized decision matrix (NDM) denoted by $\tilde{A}^*$ is $\tilde{A}_{ij}^* = [(\tilde{a_{ij}}^{l^*}, \tilde{a_{ij}}^{l'^*}), \tilde{a_{ij}}^{m^*}, (\tilde{a_{ij}}^{u'^*}, \tilde{a_{ij}}^{u^*})]$ and its entries are defined as in Equations (15)–(19).

$$a_{ij}^{l^*} = \frac{a_{ij}^{l}}{\sqrt{\sum_{i=1}^{r}[(a_{ij}^{l})^2 + (a_{ij}^{m})^2 + (a_{ij}^{u})^2]}} \tag{15}$$

$$a_{ij}^{l'^*} = \frac{a_{ij}^{l'}}{\sqrt{\sum_{i=1}^{r}[(a_{ij}^{l'})^2 + (a_{ij}^{m'})^2 + (a_{ij}^{u'})^2]}} \tag{16}$$

$$a_{ij}^{m} = \frac{a_{ij}^{m}}{\sqrt{\sum_{i=1}^{r}[(a_{ij}^{l})^2 + (a_{ij}^{m})^2 + (a_{ij}^{u})^2]}} \tag{17}$$

$$a_{ij}^{u'^*} = \frac{a_{ij}^{u'}}{\sqrt{\sum_{i=1}^{r}[(a_{ij}^{l'})^2 + (a_{ij}^{m'})^2 + (a_{ij}^{u'})^2]}} \tag{18}$$

$$a_{ij}^{u^*} = \frac{a_{ij}^{u}}{\sqrt{\sum_{i=1}^{r}[(a_{ij}^{l})^2 + (a_{ij}^{m})^2 + (a_{ij}^{u})^2]}} \tag{19}$$

Step 3: Formulation of the weighted normalized decision matrix (WNDM)

Here, we obtain the weight of each criterion. These weights are specified by different types of weight methods. The experts determine this to achieve the weight matrix W.

We multiply weight with the NDM $\tilde{A}^*_{ij}$. The WNDM is denoted by $\tilde{G}$ and can be calculated using Equations (21)–(23).

$$\tilde{g}_{ij} = [(g^l_{ij}, g^{l'}_{ij}), g^m_{ij}, (g^{u'}_{ij}, g^u_{ij})] \tag{20}$$

$$\tilde{g}^l_{ij} = w_j a^{l*}_{ij}, \tilde{g}^{l'}_{ij} = w_j a^{l'*}_{ij} \tag{21}$$

$$\tilde{g}^m_{ij} = w_j a^{m^*}_{ij} \tag{22}$$

$$\tilde{g}^u_{ij} = w_j a^{u^*}_{ij}, \tilde{g}^{u'}_{ij} = w_j a^{u'^*}_{ij} \tag{23}$$

Step 4: Normalized performance value Computation

Once the WNDM is obtained, the performance values of the NDM must be computed. The Equation (24) shows the definition and computation of the performance values of the normalized alternatives. Here, positive (benefit) and negative (cost) criteria are q and $n - q$, respectively.

$$\tilde{b}_i = \sum_{j=1}^{q} \tilde{g}_{ij} - \sum_{j=q+1}^{n} \tilde{g}_{ij} \tag{24}$$

where, $\sum_{j=1}^{q} \tilde{g}_{ij}$: Benefit criteria for $1, \ldots, q$ and $\sum_{j=q+1}^{n} \tilde{g}_{ij}$: Cost criteria for $q + 1, \ldots, n$.

Stpe 5: Defuzzification

As per the algorithm, we get the normalized performance values as fuzzy numbers. The conversion of these fuzzy numbers, viz., the defuzzification, is done using Equation (26). These numbers are denoted as Best Non-fuzzy Performance (BNP) numbers. [32].

$$\tilde{b}_i = \left((b^l_i, b^{l'}_i), b^m_i, (b^{u'}_i, b^u_i)\right) \tag{25}$$

$$BNP_i(b_i) = \frac{(b^u_i + b^{u'}_i + b^m_i + b^{l'}_i + b^l_i)}{5}. \tag{26}$$

4.2.3. Fuzzy Reference Point

The fuzzy RP approach is developed from the fuzzy RS ([64]). The symbol $\tilde{o}$ denotes the reference point. The jth fuzzy component of the RP is denoted by the pair $\tilde{A}^+_j$ and $\tilde{A}^-_j$. Equation (27) provides the computational requirement of these pairs.

$$\begin{aligned} \tilde{A}^+_j &= \left(max_i(a^{l*}_{ij}, a^{l'^*}_{ij}), max_i a^{m^*}_{ij}, max_i(a^{u'^*}_{ij}, a^{u^*}_{ij})\right) \\ \tilde{A}^-_j &= \left(min_i(a^{l*}_{ij}, a^{l'^*}_{ij}), min_i a^{m^*}_{ij}, min_i(a^{u'^*}_{ij}, a^{u^*}_{ij})\right) \end{aligned} \tag{27}$$

We need to estimate the multiplier alternatives by the weight corresponding to each criterion (z). This is achieved through the computation of the the distances between all the NDM inputs and the RPs.

To achieve this, the $Min - Max$ criterion proposed by Tchebycheff is used (Balezentis et al. [34]). The criterion is calculated using Equation (28) [65].

$$min_i \left(max_j W_j \times d(\tilde{o}_j, \tilde{a}^*_{ij}) \right) \tag{28}$$

where W_j is the jth criterion weight with $\sum_{j=1}^{n} W_j = 1$. The distance operator is d. It is the distance between the corresponding criterion values in each alternative and the optimal reference point.

Here, the best alternative is the one with its maximum distance for each of the criteria from the corresponding value in the alternative.

4.2.4. Fuzzy FMF

In the FMF approach, the total utility of the ith alternative is estimated using the Equation (29) [32].

$$\tilde{F}_i' = \frac{\tilde{P}_i}{\tilde{N}_i} \tag{29}$$

Here, $\tilde{P}_i = (P_{i1}, P_{i2}, P_{i3}) = \prod_{j=1}^{q} \tilde{a}_{ij}, i = 1, 2, \ldots, r$ denote the product of ith alternative element which corresponds to the benefit criterion. This has to be maximized. Then, $\tilde{N}_i = (N_{i1}, N_{i2}, N_{13}) = \prod_{j=q+1}^{n} \tilde{a}_{ij}, i = 1, 2, \ldots, r$ denote the product of ith alternative element which is corresponding to the cost criterion. This has to be be minimized. At the end of overall utility of each of the alternatives is denoted by $\tilde{F}_i'$. Based on the BNP value for each of the alternatives, this is computed using Equation (26).

In the fuzzy MULTIMOORA method, in the results according to the aggregation, alternatives are ranked. We consider the following fundamental assumptions.

- To cluster the results, the approaches RS, RP, and FMF are of the same importance [66].
- To calculate the final ranking, regardless of the score of each of the alternatives in the individual methods, use all available alternatives in each method that is considered the basis for aggregation [66].

However, the two basic assumptions may not be realistic under certain conditions. Moreover, they do not satisfactorily reflect the actual variation of the criteria in the final aggregation. This is a restriction of the fuzzy MULTIMOORA method. More details about the restriction of the fuzzy MULTIMOORA and some examples can be found in [43].

4.3. Correlation Coefficient and Standard Deviation (CCSD)

Multi-criteria decision making is the method of identifying and selecting the most effective alternative from the known options based on well-defined criteria. As per this notion, the criteria are not the only ones that determine the decision making. The weight is also a key factor in the MCDM process. Until now, various methods have been proposed to determine the weight of the MCDM method. In this paper, we consider a type of objective weighting model, viz., the CCSD model. The recently used method to find the weight of each criterion in the decision-making process is the CCSD model. This model was introduced by Wang and Luo. The CCSD is based on a combination of CCSD of each criterion. The proposed model has numerous advantages compared to other objective weight finding models. There is no doubt that this is a novel approach in finding the weight of each criterion. Perhaps the most important advantage is that there is no require for a particular method for normalization as opposed to the entropy method. This method is more comprehensive and reliable in determining weights than the entropy and the SD model. This has a more explicit mechanism than the critical model. The CCSD has some advantages over other similar moel, examples of which are outlined in Wang and Luo, 2010 ([44]). The procedure for finding each criterion weight using the CCSD model is described as follows.

A decision matrix is formed as $C = (c_{ij})_{s\times t}$, to evaluate s alternatives, $M_1, M_2, \ldots, M_s$, based on the t criteria, $H_1, H_2, \ldots, H_t$. The entry of the matrix c_{ij} denotes the performance of the alternative M_i based on H_j. Owing to the inability to compare the criterion with different measurement units, it is necessary in normalizing the DM that is given as $C = (c_{ij})_{s\times t}$. The normalizing method for the benefit and cost criteria is given in Equations (30) and (31).

$$z_{ij} = \frac{a_{ij} - a_{ij}^{min}}{a_j^{max} - a_j^{min}}, i = 1, 2, \ldots, s, j \in \Omega_+ \tag{30}$$

$$z_{ij} = \frac{a_{ij}^{max} - a_{ij}}{a_j^{max} - a_j^{min}}, i = 1, 2, \ldots, s, j \in \Omega_- \tag{31}$$

where $a_{ij}^{min} = min_{1\leq i\leq s}\, a_{ij}, a_{ij}^{max} = min_{1\leq i\leq s}\, a_{ij}$. Here, the benefit criteria is denoted as Ω_+ and the negative criteria is denoted as Ω_-. The normalized decision matrix entry is z_{ij}. It is in the form of Equation (32).

$$\tilde{Z} = (z_{ij})_{s\times t} = \begin{array}{c} \\ M_1 \\ M_2 \\ \vdots \\ M_s \end{array} \begin{array}{c} \begin{array}{cccc} H_1 & H_2 & \ldots & H_t \end{array} \\ \begin{pmatrix} z_{11} & z_{12} & \ldots & z_{1s} \\ z_{21} & z_{22} & \ldots & z_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ z_{t1} & z_{t2} & \ldots & z_{st} \end{pmatrix} \end{array} \tag{32}$$

The criteria weight vector is $W = (w_1, w_2, \ldots, w_t)$ that satisfies $W \geq 0$ and equation

$$\sum_{j=1}^{t} w_j = 1. \tag{33}$$

The performance value of each of the alternatives is calculated using Equation (34) using the SAW method [67].

$$\Theta_i = \sum_{j=1}^{t} z_{ij} w_j, i = 1, 2, \ldots, s \tag{34}$$

The Θ_i are the linear functions of criteria weights and the alternatives that have the highest performance values, and have greater preference compared to others. This is the best alternative (option) with the overall performance value.

Now, the criterion H_j is eliminated from the criteria to consider its impact on DM. When the criterion H_j is eradicated, the overall performance value of each alternative is redefined in Equation (35)

$$\Theta_{ij} = \sum_{x=1, x\neq j}^{s} z_{ix} w_x, i = 1, 2, \ldots, s \tag{35}$$

The correlation coefficient between the value of H_j and the overall performance value is expressed in Equation (36).

$$R_j = \frac{\sum_{i=1}^{s}(z_{ij} - \tilde{z}_j)(\Theta_{ij} - \tilde{\Theta}_j)}{\sqrt{\sum_{i=1}^{s}(z_{ij} - \tilde{z}_j)^2 . \sum_{i=1}^{s}(\Theta_{ij} - \tilde{\Theta}_j)^2}}, j = 1, 2, \ldots, t \tag{36}$$

Now, the values of $\tilde{z}_j$ and $\tilde{\Theta}_j$ are computed using Equations (37) and (38).

$$\tilde{z}_j = \frac{1}{n}\sum_{i=1}^{s} z_{ij}, j = 1, 2, \ldots, t \tag{37}$$

$$\tilde{z}_j = \frac{1}{n}\sum_{i=1}^{s} d_{ij} = \sum_{x=1, x\neq j}^{t} \tilde{z}_x w_x, j = 1, 2, \ldots, t \tag{38}$$

If R_j is big enough and near to one, then H_j and the final execution without the addition of H_j will have the identical numerical distribution and ranking. In this case, the removal of the criterion H_j has some impact on decision. It ought to have a very low weight. If R_j is very small and near to minus one, then H_j will have reverse numerical distribution and ranking. In this case, the removal of the criterion H_j has a great impact on decision and it should be given a more important weight. With reference to the above analysis, the criterion's weight is defined as

$$w_j = \frac{\sigma\sqrt{1-R_j}}{\sum_{x=1}^{m}\sigma_x\sqrt{1-R_x}}, j = 1, \ldots, t \tag{39}$$

where the SD of the criterion H_j, σ_j, is is to be determined by the Equation (40).

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{j=1}^{s}(z_{ij} - \tilde{z_{ij}})^2}, j = 1, \ldots, t \tag{40}$$

The root value of $1 - R_j$ helps to minimize the difference between the biggest and the smallest weight obtained. Equation (41) is a non-linear equation system consisting of t equations, each determined separately by t weight variables. To solve this equation, it can be converted to a nonlinear optimization model of the Equation (41).

$$\begin{aligned} &\text{Minimize } \ J = \sum_{j=1}^{t}\left(w_j - \frac{\sigma\sqrt{1-R_j}}{\sum_{x=1}^{m}\sigma_x\sqrt{1-R_x}}\right)^2 \\ &\text{Subject to } \ \sum_{j=1}^{t} w_j = 1 \quad w_j \geq 0, j = 1, \ldots, t \end{aligned} \tag{41}$$

5. Improved Fuzzy MULTIMOORA Method—Proposed Modified Method

The improved fuzzy MULTIMOORA method is obtained from the combination of the CCSD and the general fuzzy MULTIMOORA model. The procedure of this method is illustrated in Figure 4. We propose the improved fuzzy MULTIMOORA procedure in the following steps.

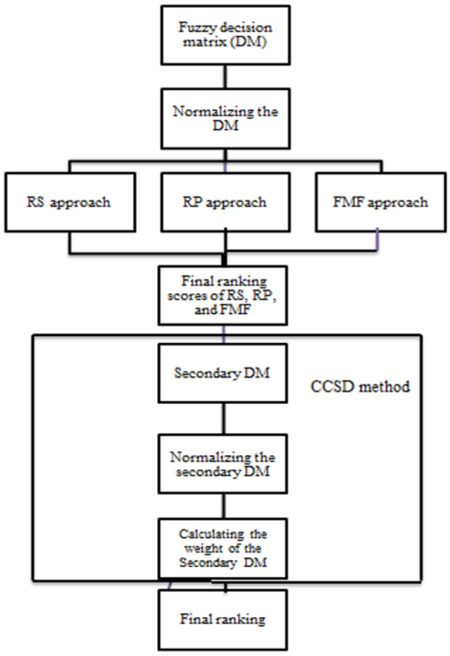

Figure 4. Improved MULTIMOORA method.

We need to estimate the weight of each method in the final aggregation. Towards this objective, the secondary decision matrix (SDM) denoted as $\ddot{A} = (\ddot{a})_{s\times 3}$, where s is the number of alternatives is used. The SDM consists of three columns consisting of the defuzzified final scores of the alternatives in the MULTIMOORA. The Equation (42) gives the working out of the secondary decision matrix.

$$\tilde{Z} = (z_{ij})_{s\times t} = \begin{array}{c} \\ M_1 \\ M_2 \\ \vdots \\ M_t \end{array} \begin{array}{c} \begin{array}{cccc} H_1 & H_2 & \dots & H_s \end{array} \\ \begin{pmatrix} \ddot{a}_{11} & \ddot{a}_{12} & \dots & \ddot{a}_{1s} \\ \ddot{a}_{21} & \ddot{a}_{22} & \dots & \ddot{a}_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ \ddot{a}_{t1} & \ddot{a}_{t2} & \dots & \ddot{a}_{st} \end{pmatrix} \end{array} \tag{42}$$

After forming the SDM, the normalizing of the matrix based on the Equations (30) and (31) of the CCSD method can be implemented. Each criterion weight is computed in the SDM after solving Equation (41). The weight is denoted by $\ddot{W}_j (j = 1, 2, 3)$ and $\ddot{W}_1$ represents the weight of the RS method, $\ddot{W}_2$ represents the weight of the RP approach, and $\ddot{W}_3$ represents the weight of the FMF approach in the final aggregation.

In the final step, the final score of each alternative is calculated using Equation (43).

$$\ddot{S} = \sum_{j=1}^{3} (\ddot{z}_{ij} \times \ddot{w}_{ij}) \tag{43}$$

where the normalized value, $\ddot{z}_{ij}$, is computed using Equations (30) and (31). The score value $\ddot{S}_i$ is based on the final ranking of the alternatives.

6. Application of Proposed Method—Numerical Illustrations

Nowadays, fast-growing countries like India face two challenges of exposure to ambient and domestic air pollution. Naturally occurring pollution does not cause many attacks in our lives because they have resurrection power, whereas pollution caused by human activities can cause great suffering.

The root cause of this is population growth and technological development. Air pollution is the second largest risk factor contributing to the disease burden in India, according to the India State-Level Disease Burden Initiative Report [9]. Complications from air pollution can include asthma, respiratory infections, stroke, lung cancer, and heart disease, according to the World Health Organization. Some of the harmful pollutants in the air we breathe include dust, chlorofluorocarbons, smoke, tobacco smoke, carbon monoxide, and many more. These contaminants affect health, and cause difficulty in breathing, shortness of breath, asthma, and the severity of existing respiratory and cardiac conditions [9]. The government and other researchers have been paying more attention to air pollution in India in recent times. India has 14 of the top 15 cities with the weakest $PM_{2.5}$ pollution. Among megacities of the world, Delhi tops the list for PM_{10} pollution (WHO, 2018). The twenty most polluted states in India are Bihar, Chhattisgarh, Chandigarh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odessa, Punjab, Rajasthan, Tamil Nadu (Chennai, Coimbatore), Uttarakhand and Uttar Pradesh (Source from Air pollution knowledge assessments). Tamil Nadu has two high level polluted cities in Chennai and Coimbatore.

According to the World Health Organization (WHO [68]) database released in April 2018 covering 100 countries between 2011 and 2016, India ranks 14 of the top 15 cities with the worst $PM_{2.5}$ pollution. Among the megacities of the world, Delhi ranks first (WHO, 2018). Chennai is the capital of Tamil Nadu, which is one of the metropolitan cities of India and it is also an important port city. After Chennai, Coimbatore is the second-largest city in Tamil Nadu. Those cities' annual standard of contamination details and sources are given below [13].

- Cities are exceeded the annual PM_{10} standard of 60 $\mu g/m^3$. The main sources of PM_{10} are the burning of coal, petrol, diesel, biomass, cow dung, and waste, as well as dust.
- Cities exceeded the annual SO_2 standard of 50 $\mu g/m^3$. The main sources of SO_2 are the burning of coal and diesel. Chennai, Pune, and Bangalore recorded high-level SO_2 absorption, indicating higher diesel consumption in personal vehicles, diesel, and trucks.
- Cities exceeded the annual NO_2 standard of 40 $\mu g/m^3$. The main sources of NO_2 are the burning of gas, diesel, and petrol-like transport emissions. Chennai, Kanpur, Jaipur, Bengaluru, Pune, and Nagpur record the greatest absorptions.

The major sources of pollution are deforestation, automobile emissions, industrial emissions, waste burning, power plants, etc. Increasing pollution is not only in the major metropolitan cities but also in medium and small cities. If these cities alter their waste management policy and facilities, such as infrastructure needs and transport, then it will help improve the air quality. Here, we discuss some emissions source options for major pollution sources in Indian cities that can evaluate the benefits of improving air quality while implementing the following alternatives. The advantages of the alternatives are obvious, there are no emissions from the alternatives, which will result in better air quality in the future. The main goal of this paper is to improve the overall air quality in Tamil Nadu, India after the implementation of these systems. This paper aims to reduce the metropolitan absorption of air contamination and gradually increase the number of annual days with good air quality. Here, we implement some methods to improve air quality in Tamil Nadu, India. These methods can effectively reduce air pollution.

In this section, the proposed MCDM method is utilized to evaluate the improving air quality in Tamil Nadu, India. The best choice to improve the air quality is obtained that has the least environmental effects and is useful for all requirements of society, to this end we selected four criteria to evaluate the five alternatives. Those criteria are environment (G_1), economy (G_2), technology (G_3), and social aspects (G_4). Here, we consider the decision-maker to be an air quality engineer, a pollution management engineer, and an environmental engineer. Then, the alternatives are *A*—Increasing Renewable Energy sources (IRES), *B*—Remanufacturing (RMA) activities, *C*—Hybrid vehicles, *D*—Dust collectors, and *E*—Increasing plantation (IP). Next, we discuss the identification of alternatives with those criteria and the selected alternatives and criteria are shown in Figure 5.

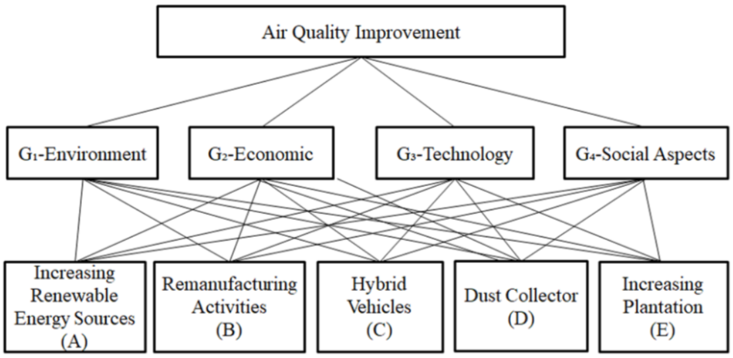

Figure 5. Air quality improvement.

6.1. Alternatives

Increasing renewable energy sources (*A*)

Renewable energy is an energy that is produced from various resources such as sunlight, rain, air, water, etc. Renewable energy will help reduce the use of fossil fuels, which is a high priority on the political agenda of countries around the world. Nowadays, renewable energy development is one of the main focuses of national and international economic, environmental, and social agendas. Renewable energy sources can contribute to improving air quality and human health. The major renewable energy sources are solar energy, wind energy, geothermal energy, hydroelectric energy, and biomass energy. All energy sources have little impact on our environment. Renewable energy will help developing countries move away from over-reliance on fossil fuels. Powerful winds, heat emanating from the earth's crust, moving water, and sunshine will guarantee a large and sustainable energy supply to a nation for many years to come.

Wind energy: Wind turbines generate electricity without directly emitting air pollution. Successful wind energy production reduces emissions of air pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NO_x) and carbon dioxide (CO_2). Wind energy has the potential to reduce the use of fossil fuels to generate electricity, which will reduce air pollution and reduce conventional pollutant emissions such as wind energy SO_2 and greenhouse gases such as CO_2. However, the air quality benefits of wind farms depend on the combination of existing energy sources. The wind energy is generated by wind turbines with low operational cost, which produces no toxic pollution or global warming emission. **Solar energy** is one of the cleanest sources of energy, which provides tremendous resources to generate clean and stable electricity without toxic pollution or global warming emissions. Generating electricity from solar panels does not produce harmful emissions. Wind energy and solar energy are clean and environment friendly energy sources. Both energies will not create any environmental issues and minimize the burning of fossil fuels. Solar panels do not emit harmful gases into the environment and the operating cost of solar energy is high compared to wind power. **Geothermal energy** is one of the oldest and most well-known sources of energy to generate electricity. Geothermal power plants do not burn fuel to generate electricity, so the amount of air pollution they emit is low. However, they need a high initial investment cost. **Hydroelectric energy:** It generates electricity by the power of flowing water. No fuel has to be burned for the process, thus causing less pollution. **Biomass energy** is the use of plant material and animal waste to generate energy. Biomass energy differs from other renewable energy sources in that it requires burning space during the process, although the carbon dioxide emitted is often balanced by the carbon dioxide captured during its own growth. It needs a low initial investment cost.

Increasing the use of renewable energy contributes to the decarbonization of the economy, while at the same time improving energy conservation and reducing greenhouse gas (GHG) emissions.

Remanufacturing activities (*B*)

Remanufacturing is an industrial process. It is one of the methods to reduce industrial pollutions. The major industrial pollutants that affect air quality are particulate matter such as volatile organic solvents, metal dust, and sulfur dioxide. Combustible wastes, especially plastics, can also produce dioxins and other hazardous chlorinated compounds. Creating a new product requires a lot of materials and energy—the raw materials must be extracted from their sources on earth. As a result, reduction and reuse are the most effective ways to save natural resources, protect the environment, and save money. Here, we can **reduce** the uses of manufacturing things with highly polluted components from industries and **reuse** the automobile components, repair broken appliances, furniture, and chemical materials, and **recycle** certain things like plastic materials (bags, bottles, etc.) newspapers, paper products, glasses. This RRR will be minimizing the pollution from burning waste things in factories. These activities also cannot generate any environmental issues and has low-level processing cost.

Hybrid vehicles (*C*)

Hybrid vehicles are vehicles that use an alternative engine or fuel that helps to reduce the automobile emissions. The motor vehicle engine emits a wide variety of pollutants, including volatile organic compounds (VOCs), carbon dioxide (CO_2), nitrogen oxides (NO_x), carbon monoxide (CO), sulfur dioxide (SO_2), lead and particulates (PM_{10}, $PM_{2.5}$). Thus, the use of alternative fuels considerably decreases harmful exhaust emissions (such as particulate matter, and sulfur dioxide, carbon dioxide, carbon monoxide), as well as ozone-producing emissions. Those hybrid vehicles are CNG vehicles, Bio-diesel vehicles, LPG vehicles, Electric vehicles (blade, fuel-cell type), methanol and ethanol vehicles. These vehicles generate low levels of carbon dioxide, NO_2, SO_2 and PM. Hybrid vehicle performance improvements require a greater upfront investment, resulting in increased economic growth and greater employment opportunities which in turn provides air quality benefits.

Dust collectors (*D*)

The dust collector is one of the ways to reduce the contamination in the atmosphere. The equipment for collecting dust, smoke, and fine particulates include scrubbers, cyclones, etc. Dust collectors are important tools in any industrial manufacturing operation. The dust collector is important to control the air quality in your plant. Some types of air pollution control equipment are used for industrial applications, and they use one or more methods to remove air pollution from industrial areas. Those are Cyclones, Scrubbers, Mist Collectors, Biofilters, Incinerators, Air Filters, Electrostatic Precipitators, Catalytic Reactors. Here, cyclone collectors are used to controlling industrial dust emissions and pre-cleaners for other kinds of collection devices. Scrubbers are usually applied in the control of dust or mist from chemical processing facilities and industry with high cost.

Increasing plantation (*E*)

Deforestation is one of the major reasons to increasing the air pollution. Trees absorb the carbon dioxide from the atmosphere. The cutting of trees pollutes the environment by increasing the carbon dioxide in the atmosphere. If we increase the plantation of road sides of urban areas and industrial areas, it will control the pollution with very low operational cost but it will take a long period. The alternatives are shown in Figure 6.

The limitation of the study: In this research work, the debate on air quality and how to improve the air quality in Tamil Nadu, India and how to deal with it better is limited to metropolitan areas. However, Tamil Nadu, India has small towns and villages. We need to look at the level of contamination in those areas, measure its extent, and understand its sources. Due to population growth and the increasing concentration of settlements, urgency is needed to deal with basic needs and air pollution. In the short term, there is a need to increase the ground surveillance network, which will help cities establish more trajectory lines of air pollution and monitor action plans, which is for villages and small towns also.

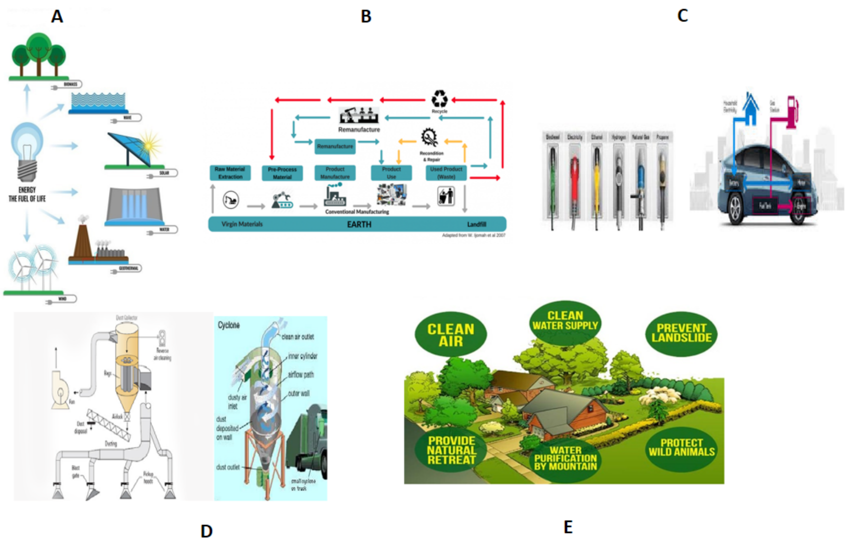

Figure 6. Alternatives: (**A**) Renewable energy sources, (**B**) Process of remanufacturing, (**C**) Alternative fuels and electric vehicle, (**D**) Dust collection devices and (**E**) Benefits of increasing plantation.

6.2. SWARA Weighting Method

The instance of the utilization of the proposed improved fuzzy MULTIMOORA is very helpful. It helps to identify the best method for improving the air quality in Tamil Nadu, India. Here, the criteria weighting is one of the important stages to solving many problems in MCDM.

The SWARA method is proposed by Kresuliene et al. [69]. The advantage of this method is estimating the accuracy of expert opinions about weights allocated by the process. The main procedure of the SWARA method is described in Figure 7 and the weight assigned to each criterion is presented in Table 6. The criteria weights are 0.2930, 0.1385, 0.3605 and 0.2078, as shown in Figure 8.

Table 6. Criteria weights using the Step Wise Weight Assessment Ratio Analysis (SWARA) method.

Criterion	α_j	$\beta_j = \alpha_j + 1$	$\gamma_j = \frac{x_{j-1}}{\beta_j}$	$W_j = \frac{\gamma_j}{\sum \gamma_j}$
G_3	0	1	1	0.3605
G_1	0.23	1.23	0.8130	0.2930
G_4	0.41	1.41	0.5765	0.2078
G_2	0.5	1.5	0.3843	0.1385

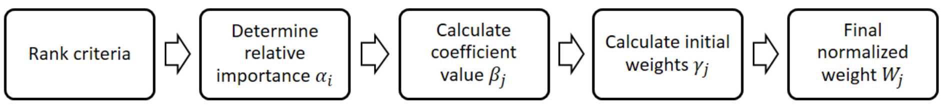

Figure 7. SWARA method.

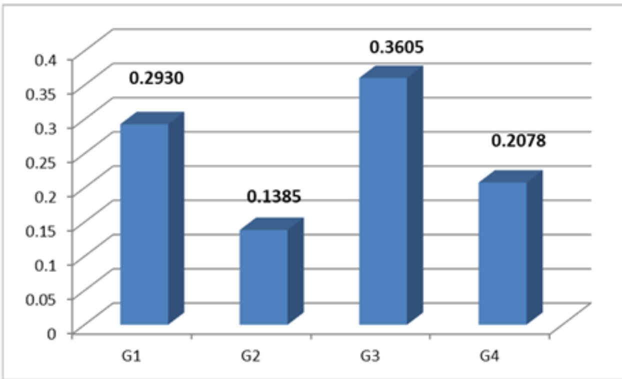

Figure 8. Weights of criteria.

6.3. Formulation of the Decision Matrix

Once the experts find the weight of the criteria, they determine the alternatives according to the present criteria. They make use of the linguistic variables in Table 3. The DM is in Table 7. At the end, the alternatives using three approaches are computed.

Table 7. Decision matrix with linguist terms.

	G_1	G_2	G_3	G_4
A	VH	VH	H	M
B	M	M	L	M
C	VH	VH	VH	H
D	M	H	M	L
E	VH	VL	VL	VH

6.3.1. Ratio System Method

In this approach, the linguistic variables are transformed to IVTFNs and it is expressed Table 3 to obtain a fuzzy DM. The initial decision matrix needs to be normalized by using Equations (15)–(19). The NDM is given in Table 8. The next step is formatting the WNDM using Equations (20)–(23). The ranking of alternatives based on the RS approach is shown in Table 9 and the ranking list of the RS approach graphical representation is shown in Figure 9.

Table 8. Normalized decision matrix.

	G_1	G_2	G_3	G_4
A	[(0.2585,0.2773), 0.3102, (0.3120,0.3274)]	[(0.2848,0.3058), 0.3418, (0.3441,0.3608)]	[(0.2466,0.2721), 0.3139, (0.3628,0.3811)]	[(0.1466,0.1693), 0.2095, (0.2540,0.2723)]
B	[(0.1206,0.1386), 0.1723, (0.2080,0.2240)]	[(0.1329,0.1529), 0.1899, (0.2294,0.2468)]	[(0.0672,0.0907), 0.1345, (0.1814,0.2018)]	[(0.1466,0.1693), 0.2095, (0.2540,0.2723)]
C	[(0.2585,0.2773), 0.3102, (0.3120,0.3274)]	[(0.2848,0.3058), 0.3418, (0.3441,0.3608)]	[(0.3363,0.3628), 0.4036, (0.4082,0.4260)]	[(0.2304,0.2540), 0.2933, (0.3386,0.3561)]
D	[(0.1206,0.1386), 0.1723, (0.2080,0.2240)]	[(0.2088,0.2294), 0.2658, (0.3058,0.3228)]	[(0.1569,0.1814), 0.2242, (0.2721,0.2948)]	[(0.0628,0.0846), 0.1257, (0.1693,0.1885)]
E	[(0.2585,0.2773), 0.3102, (0.3120,0.3274)]	[(0.0,0.0), 0.0379, (0.0764,0.0949)]	[(0.0,0.0), 0.0448, (0.0907,0.1121)]	[(0.3142,0.3386), 0.3771, (0.3810,0.3980)]

Table 9. Ranking list for the Ratio System (RS) method.

Alternatives	$\tilde{p}_i$	BNP	Rank
A	[(0.145,0.1667),0.2001,(0.2325,0.2503)]	0.1989	2
B	[(0.0558,0.0766),0.116,(0.1578,0.1764)]	0.1165	5
C	[(0.1948,0.217),0.2498,(0.2665,0.2839)]	0.2424	1
D	[(0.0601,0.0811),0.1205,(0.1623,0.182)]	0.1212	4
E	[(0.1278,0.141),0.18,(0.2031,0.219)]	0.1741	3

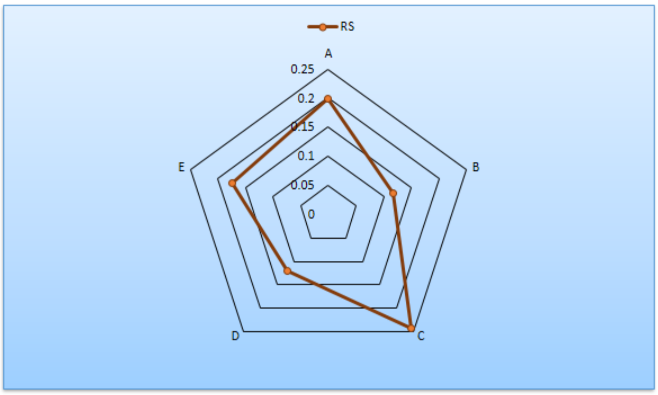

Figure 9. RS method.

6.3.2. Reference Point Method

In this approach, at first we calculate the RP vector $\tilde{o}$ using Equation (27) and it is represented in Table 10. In the following step, the distances between NDM and RP are calculated, as shown in Table 11. Then the weighted distance between the NDM and RP is calculated, as displayed in Table 12. The final ranking list for RP approach and weights are shown in Table 13 and the ranking list of the RP approach graphical representation is shown in Figure 10.

Table 10. Reference point vector ($\tilde{o}$).

	G_1	G_2	G_3	G_4
$\tilde{o}$	[(0.2585,0.2773), 0.3102, (0.3120,0.3274)]	[(0.0,0.0), 0.0379, (0.0764,0.0949)]	[(0.3363,0.3628), 0.4036, (0.4082,0.4260)]	[(0.3142,0.3386), 0.3771, (0.3810,0.3980)]

Table 11. The distance between the Normalized Decision Matrix (NDM) and the Reference Point (RP) corresponding to the criteria.

	G_1	G_2	G_3	G_4
A	[(−0.0689,−0.0347), 0, (0.0347,0.0689)]	[(−0.3608,−0.3441), −0.3039, (−0.2294,−0.1899)]	[(−0.0448,0), 0.0897, (0.1361,0.1794)]	[(0.0419,0.0846), 0.1676, (0.2117,0.2514)]
B	[(0.0345,0.0693), 0.1379, (0.1734,0.2068)]	[(−0.2468,−0.2294), −0.152, (−0.3175,−0.3588)]	[(0.0419,0.0846), 0.1676, (0.2117,0.2514)]	[(0.1466,0.1693), 0.2095, (0.2540,0.2723)]
C	[(−0.0689,−0.0347), 0, (0.0347,0.0689)]	[(−0.3608,−0.3441), −0.3039, (−0.2294,−0.1899)]	[(−0.0897,−0.0454), 0, (0.0454,0.0897)]	[(−0.0419,0), 0.0838, (0.127,0.1676)]
D	[(0.0345,0.0693), 0.1379, (0.1734,0.2068)]	[(−0.3228,-0.3058), −0.2279, (−0.153,−0.1139)]	[(0.0415,0.0907), 0.1794, (0.2268,0.2691)]	[(0.1257,0.1693), 0.2514, (0.2964,0.3352)]
E	[(−0.0689,−0.0347), 0, (0.0347,0.0689)]	[(−0.0949,−0.0764), 0, (0.0764,0.0949)]	[(0.2242,0.2721), 0.3588, (0.4082,0.4260)]	[(−0.0838,−0.0424), 0, (0.0424,0.0838)]

Table 12. The weighted distance between the NDM and reference point.

	G_1	G_2	G_3	G_4
A	[(−0.0201,−0.0101), 0, (0.0101,0.0201)]	[(−0.0499,−0.0476), −0.0420, (−0.0317,−0.0263)]	[(−0.0161,0), 0.0323, (0.0490,0.0646)]	[(0.0087,0.0175), 0.0348, (0.0439,0.0522)]
B	[(0.0101,0.0203), 0.0404, (0.0508,0.0605)]	[(−0.0341,−0.0317), −0.0210, (−0.0105,−0.0052)]	[(0.0484,0.0653), 0.0970, (0.1144,0.1293)]	[(0.0087,0.0175), 0.0348, (0.0439,0.0522)]
C	[(−0.0201,−0.0101), 0, (0.0101,0.0201)]	[(−0.0499,−0.0476), −0.0420, (−0.0317,−0.0263)]	[(−0.0323,−0.0163), 0, (0.0163,0.0323)]	[(−0.0087,0), 0.0174, (0.0263,0.0348)]
D	[(0.0101,0.0203), 0.0404, (0.0508,0.0605)]	[(−0.0447,−0.0423), −0.0315, (−0.0211,−0.0157)]	[(0.0149,0.0326), 0.0646, (0.0817,0.0970)]	[(0.0261,0.0351), 0.0522, (0.0615,0.0696)]
E	[(−0.0201,−0.0101), 0, (0.0101,0.0201)]	[(−0.0131,−0.0105), 0, (0.0105,0.0131)]	[(0.0808,0.0980), 0.1293, (0.1471,0.1535)]	[(−0.0174,−0.0088), 0, (0.0088,0.0174)]

Table 13. The final ranking list for the RP method.

Alternatives	z	BNP	Rank
A	[(0.0087,0.0175),0.0348,(0.0439,0.0522)]	0.0314	2
B	[(0.0484,0.0653),0.0970,(0.1144,0.1293)]	0.0908	4
C	[(−0.0087,0),0.0174,(0.0263,0.0348)]	0.0139	1
D	[(0.0261,0.0351),0.0522,(0.0615,0.0696)]	0.0489	3
E	[(0.0808,0.0980),0.1293,(0.1471,0.1535)]	0.1217	5

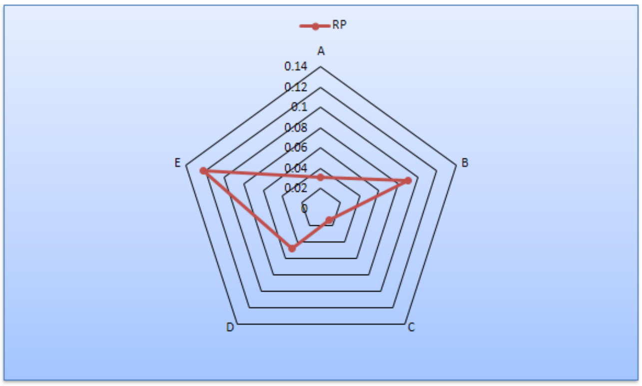

Figure 10. The RP method.

6.4. Full Multiplicative Form

In FMF, the overall utilities of the alternatives are calculated using Equation (29) and the calculated values of each alternative and the final ranks are also presented in Table 14 and the ranking list of the FMF approach graphical representation is shown in Figure 11. In the MULTIMOORA method, the overall rank list for each alternative under the dominance theory is shown in Table 15 and the overall ranking list of MULTIMOORA method graphical representation is shown in Figure 12.

Table 14. Full Multiplicative Form (FMF) approach.

	$\tilde{A}_i$	$\tilde{B}_i$	$\tilde{U}_i$	BNP	Rank
A	[(0.2724,0.2968), 0.3376, (0.3709,0.3884)]	[(0.8403,0.8486), 0.8618, (0.8626,0.8683)]	[(0.3137,0.3440), 0.3917, (0.4370,0.4622)]	0.3897	2
B	[(0.1364,0.1631), 0.2094, (0.2565,0.2766)]	[(0.7561,0.7709), 0.7944, (0.8155,0.8238)]	[(0.1655,0.2), 0.2635, (0.3327,0.3658)]	0.2655	3
C	[(0.3347,0.3584), 0.3965, (0.4109,0.4276)]	[(0.8403,0.8486), 0.8618, (0.8486,0.8683)]	[(0.3854,0.4154), 0.4600, (0.4842,0.5088)]	0.4507	1
D	[(0.1562,0.1812), 0.2264, (0.2729,0.2936)]	[(0.8049,0.8155), 0.8323, (0.8486,0.8550)]	[(0.1826,0.2135), 0.2720, (0.2808,0.3647)]	0.2627	4
E	[(0.0,0.0), 0.1891, (0.2448,0.2704)]	[(0.0,0.0), 0.6355, (0.7003,0.7216)]	[(0.0,0.0), 0.2975, (0.0,0.0)]	0.0595	5

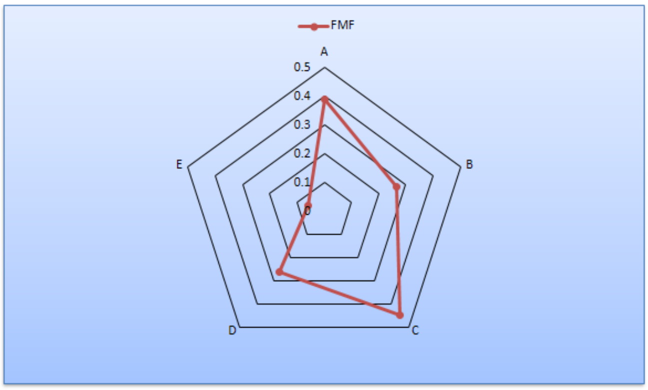

Figure 11. FMF method.

Table 15. Ranking list using Dominance theory.

	RP	RS	FMF	Rank
A	2	2	2	2
B	4	5	3	3
C	1	1	1	1
D	3	4	4	4
E	5	3	5	5

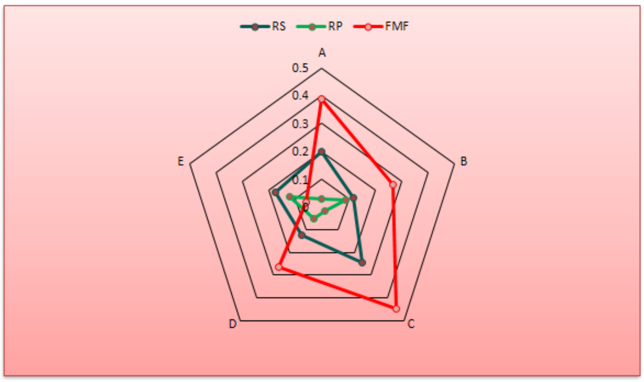

Figure 12. MULTIMOORA method.

6.5. CCSD Method

As described in this paper, once the rank of each alternative in the MULTIMOORA method is found, the SDM as presented in Table 16 is to be formed. Here in this step, we can find the weight of the method using Equation (41). They are $0.2387, 0.5561$ and 0.2051. After the computation of the weights, the SDM is necessary to normalize matrix by using Equations (30) and (31), and is multiplied by those weights to find the weighted normalized secondary decision matrix presented in Table 17.

Table 16. The secondary decision matrix.

	Refernce Point	Ratio System	FMF
A	0.0314	0.1989	0.3897
B	0.0908	0.1165	0.2655
C	0.0139	0.2424	0.4507
D	0.0489	0.1212	0.2627
E	0.1217	0.1741	0.0595

Table 17. The weight normalized secondary decision matrix.

	Refernce Point	Ratio System	FMF
A	0.1999	0.3639	0.1731
B	0.0684	0	0.1079
C	0.2387	0.5561	0.2051
D	0.1611	0.0207	0.1065
E	0	0.2544	0

Finally, using (43), the overall performance value and the final ranks of each alternative value are computed as shown in Table 18 and the final ranking list of CCSD model graphical representation is shown in Figure 13.

Table 18. The performance value and final rank of each of the alternatives.

Alternatives	Performance Value	Final Rank
A	0.7369	2
B	0.1763	5
C	0.9999	1
D	0.2883	3
E	0.2544	4

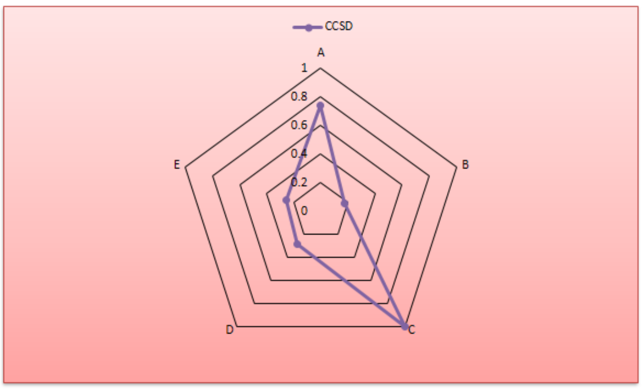

Figure 13. Correlation Coefficient and Standard Deviation (CCSD) method.

The comparison of the results of the fuzzy MULTIMOORA model and final aggregation is performed using the theory of dominance. These outcomes are shown in Table 19. There are some differences in the final ranks of the alternatives. The MULTIMOORA system has three approaches viz., RS, RP, and FM. Combining the teams of that approach is the dominant theory, which is given in the ranking column by dominance theory. The efficient use of the CCSD model in the fuzzy MULTIMOORA provides the final ranks of this study. This is available in the last column of Table 19. Here, alternatives B and D have different ranks by the dominance theory. Nevertheless, by the proposed method, the remaining alternatives have the same ranks.

Table 19. Ranking list.

Alternatives	RP	RP	FMF	Ranking by Dominance Theory	Ranking by Proposed Method
A	2	2	2	2	2
B	4	5	3	3	5
C	1	1	1	1	1
D	3	4	4	4	3
E	5	3	5	5	4

From Table 19, the best alternative is C-Hybrid vehicles. This is the best and quickest way to control the air pollution. It helps to improve the air quality in Tamil Nadu, India. In India, air quality has been improving despite the COVID-19 lockdown, because of no vehicle emissions in the lockdown period. Therefore, changing to alternative fuel and hybrid vehicles will help to improve the air quality. It is one of the great ways to improve air quality in Tamil Nadu, India.

7. Sensitivity Analysis and Comparison Analysis

7.1. Sensitivity Analysis

The sensitivity analysis of air quality improving alternatives with the proposed method is shown in this section according to the three cases of weights that are shown in Table 20 and the graphical representation given in Figure 14. For the sensitivity analysis of this model, the results of three cases are compared and the graphical representation is shown in Figure 15. Here, **Case 1** is the result of this study, and Case 2 and Case 3 are the other results, which are found using the different weights of the criteria. In this paper, the selection of air quality improving method is based on four criteria, which are G_1—environment, G_2—economic, G_3—technology, and G_4—social. Moreover, for finding the initial weights of four criteria, here the SWARA method is used. The detailed weighting method proposed in this study gives full attention to the opinions of experts and assessment information in weight determination, which approaches the ranking of the data in practice. For finding the alternative ranks, the improved fuzzy MULTIMOORA method is used. The final ranks are based on the weights of each criterion, which is found by the CCSD objective weight finding method. In improving air quality selection, the best alternative can be found when examining not only positive criteria such as technology, social features, and environment, but also negative criteria. When criteria are important, then those can create a better compromise alternative.

Table 20. Weights in sensitivity analysis.

Alternatives	Case 1	Case 2	Case 3
A	0.7369	0.7998	0.5435
B	0.1763	0.347	0.4852
C	0.9999	0.9819	0.7875
D	0.2883	0.254	0.2411
D	0.2544	0.5820	0.4811

Case 2: Here, economic is the negative criteria. Economic is one of the most important criterion in improving air quality application. We cannot undertake air quality on a purely cost basis. So we

consider the weights of criteria are $G_1 = 0.2078, G_2 = 0.3605, G_3 = 0.1385$ and $G_4 = 0.2930$ respectively. In this case, the ranking order is follows as:

$$C > A > B > E > D$$

when G_2 is 0.3605.

Case 3: Here, we consider the weights of criteria are $G_1 = 0.3605, G_2 = 0.2930, G_3 = 0.2078$ and $G_4 = 0.1385$ respectively. In this case, the ranking order is follows as:

$$C > A > E > B > D$$

when G_2 is 0.2930.

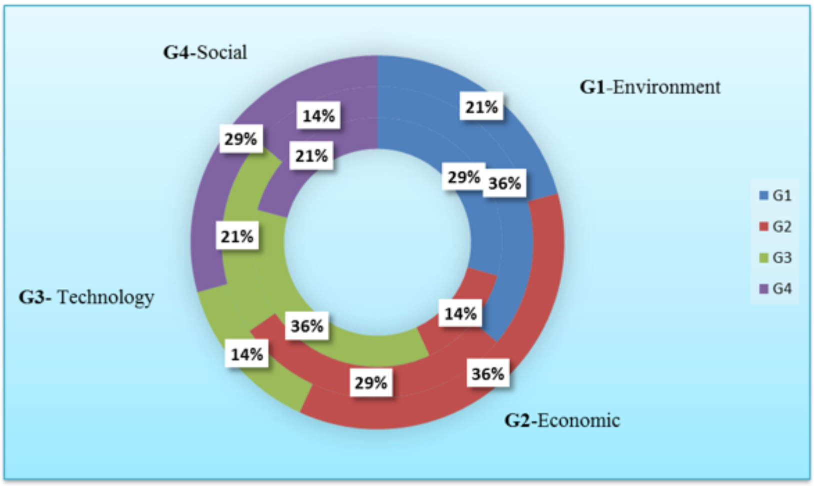

Figure 14. Weights of three cases.

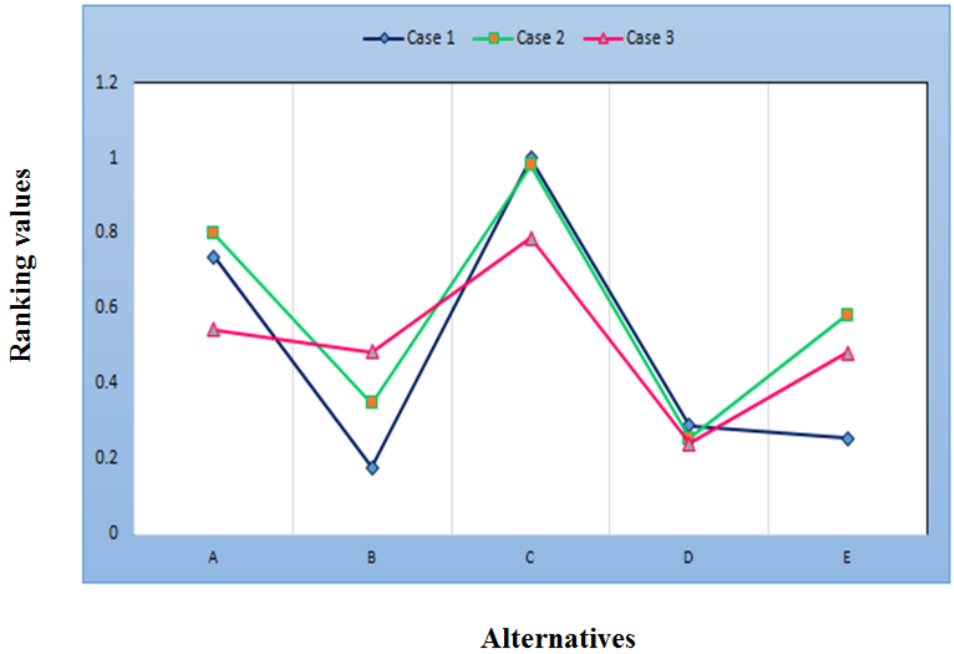

Figure 15. Results of sensitivity analysis.

In Table 21, alternative A as per the three cases has the same rank (2). Alternative B as per Case 1 is ranked (5), Case 2 is ranked (4), and Case 3 is positioned in rank (3). Alternative C as per the three cases has the same rank (1), and hence alternative C is the best solution in all three cases. Alternative D as per Case 2 and 3 has the fifth rank, whereas according to Case 1, it is positioned in rank (3). Alternative E as per Case 1 and Case 3 has the rank (4), and in Case 2, its rank is (3). Therefore, the above three cases show that they are based on the importance of the optimal alternative economy for improving air quality. Furthermore, its significance is based on the criterion weight, which indicates that the ranking sequence changes as the weight values of the criteria change. So in terms of sensitivity, we hope that we can select the best alternative to improve air quality if there is a weight detection system based on the importance given in these cases.

Table 21. Sensitivity analysis results.

Alternatives	Case 1	Rank	Case 2	Rank	Case 3	Rank
A	0.7369	2	0.7998	2	0.5435	2
B	0.1763	5	0.347	4	0.4852	3
C	0.9999	1	0.9819	1	0.7875	1
D	0.2883	3	0.254	5	0.2411	5
E	0.2544	4	0.5820	3	0.4811	4

7.2. Comparison Analysis

In this study, the proposed improved fuzzy MULTIMOORA is compared with the TOPSIS and VIKOR. In this paper, the comparison analysis presents more reasonable and robust results compared with other methods. Therefore, the ranking results obtained by the proposed method are more scientific and applicable than those obtained by the TOPSIS and VIKOR models. From Table 22, the ranking lists of the three methods are different. This shows that the results calculated using the proposed ones are somewhat similar to the existing methods. The proposed criteria weights are applied to other existing MCDM methods. Here, the weights are achieve from the SWARA and CCSD models. The comparison results of ranking order is given in Table 23. The results of the proposed ranking are different from the existing TOPSIS and VIKOR model. Therefore, more exact results can be obtained by using the proposed approach compared with other MCDM models. In this paper, we considered only four criteria for evaluating alternatives, and future studies may use the proposed approach considering several criteria such as operational cost, health risk, society benefits, and safe criteria.

Table 22. Ranking list of comparison analysis.

Alternatives	Proposed	Rank	TOPSIS	Rank	VIKOR	Rank
A	0.7369	2	0.6122	1	0.9914	1
B	0.1763	5	0.3307	5	0.3659	4
C	0.9999	1	0.5745	2	0.5821	3
D	0.2883	3	0.4413	3	0.9807	2
E	0.2544	4	0.3948	4	0.1668	5

Table 23. Ranking order of comparison analysis.

Methods	Ranking
Proposed method	$C > A > D > E > B$
TOPSIS	$A > C > D > E > B$
VIKOR	$A > D > C > B > E$

8. Conclusions

There are two levels of finding solutions to the problems faced by the humanity. At first, it is by the personal decisions taken by the individuals. This can be achieved by continuous education, awareness programmes, promotion of environment protection activities, etc. However, the grass-root level works might not be the only method of solution. A strong policy decision enacted and implemented by various nations promoted and campaigned with the help of the internal agencies is a must in this age. Human resources and material resources have to be pooled to build a strong Research and Development backbone to support matters that concern the environment. In this process, humans and human organizations have to make decisions based on various criteria and situations to solve the many problems that surround them. The results are always complex due to several and sometimes conflicting criteria, which may lead to the development of different conditional decision-making (MCDM) systems. Multi-criteria analysis is becoming increasingly important as a means of constructing consensus in order to communicate air pollution control planning to decision-makers and the public. The MULTIMOORA method is the most popular multi criteria decision making method introduced by Brauers and Zavadskas [63], which increases the robustness of the MOORA method. This method is a completely effective method for evaluating and ranking alternatives in various instances without subjective orientation. In this paper, we have increased the proficiency and accuracy of the fuzzy MULTIMOORA using the CCSD method with the normalized interval-valued triangular fuzzy numbers. The proposed method is used to choose the best alternatives based on a number of criteria. We find that the best way to protect air quality is to reduce the emission of pollutants by changing to cleaner fuels and processes. Hence, the improved MULTIMOORA with CCSD method has been applied to choose the best alternative for protect air quality in Tamil Nadu, India based on four criteria. The alternative C-Hybrid vehicle is the best alternative using the proposed mathematical model. We need to bring out policy changes in alternative fuel or hybrid engine for reducing pollution to the atmosphere. This is the quickest way to reduce the pollution in Tamil Nadu, India comparing with other alternatives.

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