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Deterministic Decision Support System for the Assessment of Cities Based on Air Quality Indicators:

Decision Support System Using DBA

Rakesh Garg, Amity University, Noida, India
https://orcid.org/0000-0001-7037-4209

Supriya Raheja, Amity University, Noida, India*

ABSTRACT

A deterministic decision support system is developed for the assessment of various Indian cities based on the air quality parameters in this research. The present study shapes the assessment of cities as a multi-criteria decision-making (MCDM) problem due to the involvement of many indicators. To solve the present assessment problem the authors use an MCDM method, namely distance-based approach (DBA), that mainly works on the Euclidean distance calculation for each city from the optimal point and ranks the cities on the basis of their calculated distances. The city scoring minimum distance value is ranked at top position, and the city with the maximum distance value at the last position.

KEYWORDS

Air Pollution, Air Quality Indicators, Assessment, Decision Support System, Distance-Based Approach (DBA), Euclidean Distance, Multi-Criteria Decision Making (MCDM), Ranking

INTRODUCTION

Air pollution has become the globally concerned environmental challenge which is disturbing the viable growth of many developing countries. It is among the top five global risk factors for mortality. IQAir 2019 (World Air Quality) report revealed that 21 worst polluted cities out of top 30 are only from India which proves the progressive deprivation in air quality of India due to the rapid evolution of resources and rapid growth of population in urban areas. Vehicular and industrial emissions, construction, road dust, and anthropogenic activities etc. (Wang et al., 2018) are the other factors which diminishes the air quality. Figure 1 demonstrates the major resources triggering air pollution in India (Wikipedia, 2019). Recent reports of the World Health Organization (WHO) stated that globally 90% of people are breathing in highly polluted air including both indoors and out-doors. However,

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*Corresponding Author

more than 80% urban population is exposed to such a poor air quality which is even exceeding the WHO (2019) guideline limits.

Over the last several decades, various studies and research have been concluding air pollution as an important risk factor to the individual's health (Liu et al., 2018; Chakrabarti et al., 2019). Poor air quality is affecting everyone's health either young or old, rich, or poor etc. According to reports, approximately 7 million premature deaths per year is caused due to both indoor and outdoor pollution. However, 4.2 million deaths are just because of outdoor pollution due to poor air quality. According to Recent Global Burden of Diseases (GBD) report India is amongst those countries who are surpassing the WHO guideline limits for air pollution. Not only among these countries, India and China are contributing more than 50% for this disease burden (Balakrishnan et al. 2019).

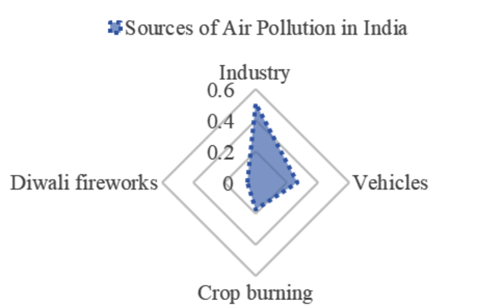
Number of studies reported that excessive contact to these harmful concentrations of pollutants may trigger many diseases like lung cancer, cardiopulmonary mortality, respiratory diseases and many more (Pope et al., 2002; Lepeule et al., 2014). PM2.5 beyond the limits may initiate lung cancer, whereas ozone beyond limits may trigger respiratory diseases (Jerret et al., 2009). The average value of PM2.5 is rapidly increasing in India (OECD, 2019). According to OECD (Organization for Economic Cooperation and Development) report, the increase in the value of PM2.5 may cause approx. 2000 person per million premature deaths in India by 2060.

Several studies have been reporting the other impacts of poor air quality on human life. Along with health (Liu et al., 2018; Chakrabarti et al., 2019), it may adversely impact on the agricultural land (Agarwal et al., 2003) and on the economy mainly for the developing nations (Lvovsky, 1998; Maji et al., 2017). Poor air quality caused around USD 30 billion economic loss in India.

To maintain the quality of air in India is a big challenge for government as well as the for the organizations. Numerous measures and technologies have been recommended and implemented to improve the quality of air (Elbir et al., 2000; Akkoyunlu & Erturk, 2002). The quality of air is referred by air quality index (AQI) and the value of AQI is majorly dependent on the presence of concentration of pollutants like PM2.5, PM10, SO2, O3 and NO2. The value of these pollutants in air can vary from time to time (Shang & Tang, 2016). Beside pollution emission, natural events also play key role in fluctuation of the concentration of these pollutants.

During the last decades, the number of spatial and statistical assessments have been carried out to evaluate the air quality (Gaga et al., 2012; Dong, & Liang, 2014; Preisler et al., 2015). The rest of the present study is organized as: Section 2 presents the various existing studies related to the air-pollution, section 3 describes the developed decision support system and section 4 demonstrates the working of developed decision support system using a suitable case study. The results obtained are validated in section 5 using Kendall's Tau test, whereas sensitivity analysis is given in section 6. Results are discussed in section 7 followed by the significance and contribution of DBA method in section 8. The implications and future scope of this study are provided in section 9.

Figure 1. Major sources of Air Pollution



LITERATURE REVIEW

This section describes the various theories and research available in the open literature that models the present assessment problem as an MCDM problem. It is a major MCDM issue since air quality is dependent on many conflicting air quality parameters. Some previous research used fuzzy-based MCDM approaches to evaluate different industries using various indicators such as PM10, PM2.5, SO2, NO2, CO2, and ozone (Lad et al., 2008; Chitnis et al., 2015). Wang et al. (2016) used an MCDM method for assessing several air pollution indicators, called Technique for order preference similarity to ideal solution (TOPSIS). The authors considered SO2, NO2, PM10, dust drops, pH, and AQI in this analysis.

Furthermore, the entropy method is combined with a back propagation neural network to calculate priority weights for all indicators to assess their effect on air pollution. TOPSIS primarily calculates distances between two ideal points (+ve and –ve) for each alternative considered for evaluation. The key flaw with this TOPSIS approach is that, even when priority weights are considered, they have little impact on the final ranking results. Sarfaraz et al. (2018) used the Complex proportional assessment (COPRAS) MCDM method to rate construction projects in the field of air pollution in their recent work. The COPRAS method has a major flaw in that it becomes unreliable and can produce large deviations in final results when minor variations in the evaluation data occur (Podvezko, 2011).

On the other hand, several researchers looked at whether various main tools were either stationary or mobile (coal-fired power plants, factories, agriculture-related emissions, construction dust, cooking fumes, river dust) mobile (diesel vehicles, scooters, ship emissions, railway transportation) causing the air pollution. Decision Making Trial and Evaluation Laborator Analytic Network Process (DANP) and VlseKriterijumska Optimi-zacija were introduced by Kou-Hsiung et al. (2019). I Kompromisno Resenje (VIKOR) conducted a ranking of various resources, focusing on the city of 'Kaohsiung,' and discovered that scooters are a key resource in mobile air pollution, whereas coal-fired power plants are a major source of stationary air pollution. However, the authors mentioned that this ranking may differ in case of other cities of Taiwan. The ANP approach focuses on pairwise comparisons of alternatives using assessment metrics, while VIKOR offers a compromise solution for MCDM problems. Sahin et al. (2020) applied analytical hierarchy process (AHP) and geographic information systems (GIS) to investigate the air pollution in Iğdır city center. They considered the 15 parameters of weather and topographic features to find the worst place for the air quality. Zeydan and Pekkaya (2021) determined the priorities of 5 air pollutants (PM10, SO2, CO, NO2 and O3) using grey relational analysis (GRA) method. They considered the data of 2019 for calculating the air quality index in Turkey. They concluded that the priority of pollutant PM10 is 2.5 times more crucial than NO2.

Despite the fact that numerous MCDM methods have been introduced to evaluate various industries and cities based on air quality indicators, there is still a need to build an efficient decision support system for this current assessment issue, according to a thorough review of the literature. With this in mind, the following are the study's main objectives:

- To determine the different air quality criteria that can be used to evaluate cities.
- To create a decision-support framework for evaluating different cities based on the criteria chosen.
- Using an appropriate case study, explain how the built decision support system works.
- Conduct a sensitivity analysis to determine the criticality of each city's air quality indicators.

DECISION SUPPORT SYSTEM FOR ASSESSMENT OF CITIES

A 3-phase strategy has been employed to design the decision support system for assessment of cities based on the air quality parameters as shown in figure 2.

Identification and Selection of Cities and Air Quality Indicators

The first phase of the developed decision support system involves the identification and selection of the cities and the air quality parameters. Total fifteen Indian cities are finally taken up for their assessment with respect to seven air quality parameters.

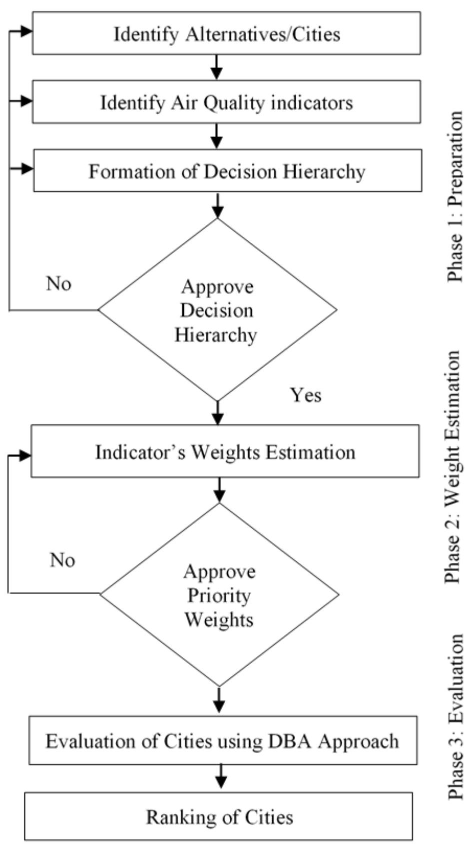
Weight Estimation

The second phase of the developed decision support system is concerned with the priority weight estimation of the air quality parameters. Here, priority weights mean "How much the weightage/ importance each air quality parameter carry in assessment process"?

Assessment of Cities

The third phase deals with the assessment of all fifteen cities with respect to seven air quality parameters using an MCDM approach. (MCDM) methods, that came into the existence in the 1970's as the powerful tools that are used to solve the various decision-making problems for which evaluation depends on many conflicting criteria. According to many authors, MCDM is referred as the branch of operation research that is based on the mathematical approaches to make some decision for any decision-making problem (Garg et al., 2013, Garg et al., 2018; Garg, 2020). Distance based approach (DBA) is implemented for the assessment of cities based on air quality parameters in this study. The available literature on the DBA method reveal that many authors have implemented this method to

Figure 2. Decision Support System for Assessment of Cities



solve numerous decision-making problems in the field of science and engineering and observed that DBA is highly capable to solve such problems in very effective and efficient way (Sharma et al., 2010; Kumar & Garg, 2010; Gupta et al. 2013; Garg et al., 2016; Garg & Jain, 2017; Garg, 2017; Gupta et al. 2018).

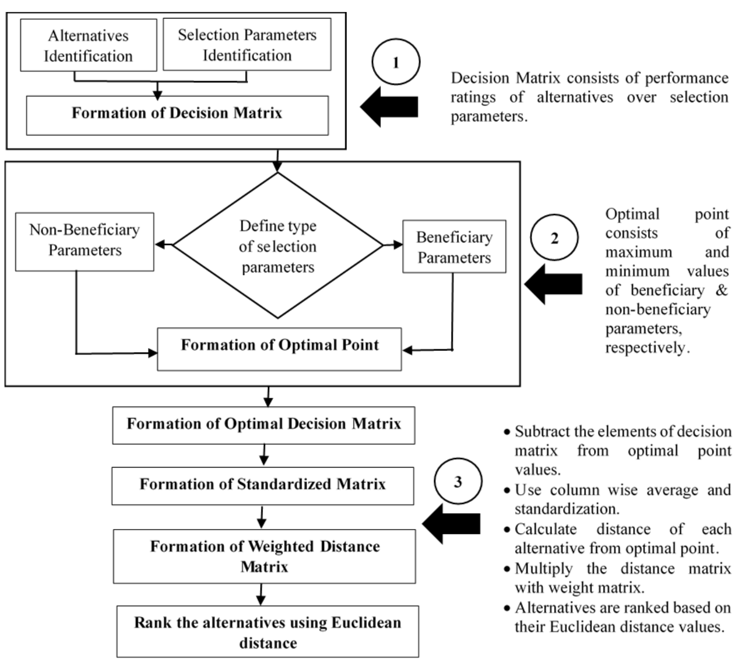
DBA mainly work on the Euclidean distance calculation for each of the city from a hypothetical point known as "optimal point". Here, optimal point contains the best values with respect to each air quality parameter. Concerning to the parameters, DBA is capable to accommodate both types of parameters as (i) Beneficiary and (ii) Non-Beneficiary. Beneficiary parameters are defined as the parameters whose maximum values are considered as the best values, whereas non-beneficiary parameters are those parameters whose minimum values are considered as the best values. So, optimal point may be referred as a hypothetical city having all optimal values with respect to each air quality parameter depending upon the parameter's type. The working concept of the DBA method is given in the figure 3. The algorithm to demonstrate the full working of the DBA method is explained below.

ALGORITHM: DISTANCE BASED APPROACH (DBA)

Consider a decision-making problem 'P' with a set of alternatives 'A' and a set of selection parameter 'C' as given below.

$$A = \left\{A_1, A_2, A_3, \ldots, A_n\right\},\ C = \left\{C_1, C_2, C_3, \ldots, C_m\right\}$$

Figure 3. Distance Based Approach (DBA)



Step 1. Initialize a decision matrix $\left[A_{ij}\right]_{n\times m}$ consisting of the ratings of 'n' alternatives w.r.t. 'm' selection parameter. Here, A_{ij} represent the rating of i^{th} alternative w.r.t. j^{th} selection parameter and $i=(1,2,3,\ldots,n)$ and $j=(1,2,3,\ldots,m)$.

Step 2. Define the criteria type and the weight of all selection parameters as:

$$\left\{C_b\right\}\in C\,;\; C_b$$

is the set of beneficiary parameters.

$$\left\{C_{nb}\right\}\in C\,;\; C_{nb}$$

is the set of non-beneficiary parameters.

$$\left[w_j\right]=\left[w_1,w_2,w_3,\ldots,w_m\right]$$

w_j is the weight of j^{th} selection parameter.

Step 3. Append the decision matrix as $\left[OPT-A_{ij}\right]_{(n+1)\times m}$

For

$$j=1\ to\ m$$

For

$$i=1\ to\ n$$

If

$$(C_j\in C_b)$$

Then

$$\left[OPT-A_{(n+1)j}\right]=\max_j(A_{ij})$$

Else

$$\left[OPT - A_{(n+1)j}\right] = \min_j (A_{ij})$$

Step 4. Now, standardize the $\left[OPT - A_{ij}\right]_{(n+1)\times m}$ to eliminate the unit differences as $\left[STD - A_{ij}\right]_{(n+1)\times m}$

For

$$j = 1 \ to \ m$$

For

$$i = 1 \ to \ n$$

$$\left[Avg_{ij}\right] = \frac{1}{n+1}\sum_{i=1}^{n+1} A_{ij}$$

$$\left[SDEV_{ij}\right] = \left[\frac{1}{n+1}\sum_{i=1}^{n+1}(A_{ij} - Avg_{ij})^2\right]^{\frac{1}{2}}$$

$$\left[STD - A_{ij}\right] = \left[\frac{(A_{ij} - Avg_{ij})}{SDEV_{ij}}\right]$$

Step 5. Append the $\left[STD - A_{ij}\right]_{(n+1)\times m}$ to find the weighted distances of each alternative from optimal point as given below.

For

$$j = 1 \ to \ m$$

For

$$i = 1 \ to \ n$$

If

$$(C_j \in C_b)$$

Then

$$\left[DIS - A_{ij}\right] = \left(\left[STD - A_{(n+1)j}\right] - \left[STD - A_{ij}\right]\right) \times \left[w_j\right]$$

Else

$$\left[DIS - A_{ij}\right] = \left(\left[STD - A_{ij}\right] - \left[STD - A_{(n+1)j}\right]\right) \times \left[w_j\right]$$

Step 6. Calculate the Euclidean distance (ED) for each alternative as:

For

$i = 1\ to\ n$

$$ED_i = \left[\sum_{j=1}^{m}\left(\left[DIS - A_{ij}\right]^2\right)\right]^{\frac{1}{2}}$$

Step 7. Rank the alternatives based on the calculated Euclidean distance.

DECISION SUPPORT SYSTEM DEMONSTRATION

This section demonstrates the step wise working of the developed decision support system in section 3. For demonstration, a sample case study is designed that aims on the assessment and ranking of fifteen Indian cities based on seven air quality indicators.

Identification of Cities and Air Quality Parameters

Total 15 Indian cities (Ghaziabad, Delhi, Noida, Gurugram, Greater Noida, Lucknow, bulandshar, Mujjafarnagar, Bagpat, Mujjaffarpur, Bhiwadi, Muradabad, Faridabad, Jind and Hissar) are considered for their assessment purpose based on 07 air quality parameters given in Table 1.

Weight Estimation of Air Quality Parameters

In this study, an assumption is made about the priority weights of the air quality parameters that all parameters have equal importance in the evaluation process. So, the weight of each air quality parameters is considered equal to each other and is taken as unity in this study.

Assessment of Cities using DBA

This section shows the stepwise implementation of the DBA algorithm presented earlier in section 3.3 of this study on a case study consisting of fifteen Indian cities and seven air quality parameters. Initially, the decision matrix consisting of the ratings of cities with respect to all air quality parameters is formed as given below.

Table 1. Description of Air quality parameters used in this study

Air Quality Parameters	Description	Sources
Particulate Matter (PM10)	Presence of particles with diameter 10mm or less in air	Motor vehicles, industries, wood burning, dust storms
Particulate Matter (PM2.5)	Presence of particles with diameter 2.5 mm or less in air	Motor vehicles, industries, wood burning, dust storms
Sulphur Dioxide (SO2)	Highly reactive gas with an irritating smell	Combustion at power plants, industries
Nitrogen Dioxide (NO2)	Highly reactive gas	Emissions from motor vehicles, industries, heaters
Carbon Monoxide (CO2)	Poisonous gas	Motor vehicles, industries, bushfires
Ozone (O3)	Highly reactive gas	Motor vehicles, industries
Air Quality Index (AQI)	Maximum of above six air quality indicators	All as above

$$\left[A_{ij}\right]_{15\times 7} = \begin{bmatrix} 187.09 & 171.76 & 36.04 & 26.44 & 8.28 & 12.41 & 205.62 \\ 182.90 & 168.87 & 28.18 & 15.03 & 35.10 & 9.31 & 200.31 \\ 201.17 & 194.69 & 69.47 & 54.63 & 8.91 & 16.46 & 219.56 \\ 161.76 & 125.84 & 8.56 & 10.17 & 25.42 & 0.00 & 162.24 \\ 167.95 & 147.80 & 37.06 & 29.90 & 9.57 & 13.48 & 171.34 \\ 149.01 & 205.89 & 14.93 & 17.31 & 1.88 & 10.71 & 148.37 \\ 158.32 & 126.45 & 39.85 & 16.31 & 11.73 & 10.54 & 152.26 \\ 150.73 & 106.66 & 29.86 & 14.99 & 10.36 & 9.83 & 151.58 \\ 167.87 & 139.82 & 40.89 & 12.07 & 6.77 & 8.88 & 180.33 \\ 161.67 & 0.00 & 47.56 & 13.21 & 10.02 & 10.40 & 157.98 \\ 174.99 & 150.46 & 21.00 & 20.89 & 15.35 & 7.17 & 188.78 \\ 165.59 & 132.27 & 29.18 & 19.98 & 8.67 & 11.27 & 172.55 \\ 156.06 & 0.00 & 43.38 & 12.07 & 37.89 & 10.79 & 153.68 \\ 154.19 & 101.93 & 28.69 & 8.32 & 3.79 & 5.36 & 157.50 \\ 158.85 & 108.76 & 27.31 & 11.88 & 9.99 & 6.67 & 166.82 \end{bmatrix}$$

Now, the optimal value for each column of the above decision matrix is obtained as (149.01, 0, 8.56, 8.32, 1.88, 0, 148.37) by assuming that all seven air quality parameters considered in this study are non-beneficiary. Hence, their minimum values are taken as the optimal values. After obtaining the optimal values, the steps (4-6) of the DBA algorithm are per-formed to obtain the Euclidean distances for all fifteen cities. The ED value for is so obtained as (6.25, 6.07, 9.33, 3.24, 5.43, 4.56, 4.32, 3.62, 4.48, 4.05, 4.48, 4.44, 5.05, 2.68, 3.15) respectively. Finally, all fifteen cities are ranked according to their Euclidean distance value as shown in figure 4.

Figure 4. Rankings of cities based on Euclidean distances using DBA method

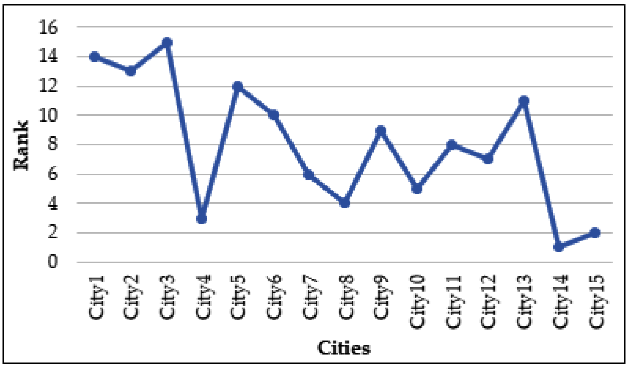


Table 2. Comparative Rankings of Cities obtained from DBA, TOPSIS and EDAS methods

Cities	DBA	TOPSIS	EDAS	Cities	DBA	TOPSIS	EDAS
	Rank	Rank	Rank		Rank	Rank	Rank
$City_1$	14	11	12	$City_9$	9	5	7
$City_2$	13	14	14	$City_{10}$	5	3	3
$City_3$	15	15	15	$City_{11}$	8	9	9
$City_4$	3	7	2	$City_{12}$	7	8	10
$City_5$	12	12	13	$City_{13}$	11	13	8
$City_6$	10	6	4	$City_{14}$	1	1	1
$City_7$	6	10	11	$City_{15}$	2	2	5
$City_8$	4	4	6				

METHODOLOGY VALIDATION

To validate the results obtained from DBA method, the problem of the assessment of 15 cities with respect to 07 air quality parameters is also solved using two other MCDM methods such as EDAS and TOPSIS. The comparative ranking results of three MCDM methods as DBA, EDAS and TOPSIS are given in Table 2.

To check the existence of the relationship between the DBA-TOPSIS and DBA-EDAS ranking results, Kendall's Tau test is performed. Kendall's tau test is referred as a rank correlation test developed by Maurice Kendall in 1938. In this test, the value of the Kendell tau coefficient is measured between the two quantity sets. The value of this coefficient always ranges from (-1) to (+1). Any value nearer to (+1) signify the strong association be-tween the two quantity sets, whereas the value nearer to (-1) signify the weak association. Further, Kendall's tau test can be implemented in three variants namely, 'Tau-a', 'Tau-b' and 'Tau-c' depending on the datasets (Bonett & Wright, 2000; McLeod, 2005; Valencia et al., 2019; Yamin et al., 2019). In the present case study, Kendall's tau-c test is implemented as 'Tau-c' is most capable to accommodate the rectangular tables. The determination of the Tau coefficient mainly depends on the sum of concordant pairs and the sum of discordant pairs calculated for given quantity sets. The formula to calculate Tau coefficient is given below.

Table 3. Kendall's Tau Statistics

	DBA-TOPSIS			DBA-EDAS		
Cities	**Concordant pairs**	**Discordant pairs**	**Tau Coefficient**	**Concordant pairs**	**Discordant Pairs**	**Tau Coefficient**
$City_1$	14	0	0.67	1 4	0	0.61
$City_2$	13	0		1 0	3	
$City_3$	8	4		1 2	0	
$City_4$	10	1		9	2	
$City_5$	10	0		1 0	0	
$City_6$	5	4		4	5	
$City_7$	6	2		4	4	
$City_8$	5	2		4	3	
$City_9$	6	0		5	1	
$City_{10}$	5	0		5	0	
$City_{11}$	2	2		4	0	
$City_{12}$	2	1		2	1	
$City_{13}$	1	1		1	1	
$City_{14}$	1	0		1	0	
$City_{15}$	0	0		0	0	

$$(\tau) = \frac{concordant - discordant}{concordant + discordant}$$

The Kendall's Tau test statistics for both cases such as (i) DBA-TOPSIS and (ii) DBA-EDAS are given in Table 3.

SENSITIVITY ANALYSIS

The major purpose of the sensitivity analysis is to explore and examine the effect of change in values of cities with respect to air quality parameters forming the input to the developed decision support system. The simplest form of the sensitivity analysis, i.e., 1-way sensitivity analysis is performed here to check the criticality of air quality indicators for each city. The values of each city with respect to air quality parameters are changed one by one with a percentage change of 20% to perform such sensitivity analysis. Such changes in the values are ranges from (-100%) to (100%) in this study. The percentage change in the Euclidean distance of each city is noted with respect to all changes going to hold in values against each air quality parameter. The sensitivity analysis graphs for each city are given in figures (5-19).

RESULTS AND DISCUSSIONS

The present study implements DBA MCDM method for the assessment of fifteen cities based on the seven air quality parameters. The major findings of the present research are discussed below. The figure 4 i.e. ranking of fifteen Indian cities w.r.t. seven air quality parameters depict that the city14

Figure 5. Sensitivity Analysis for City$_1$ 'Ghaziabad'

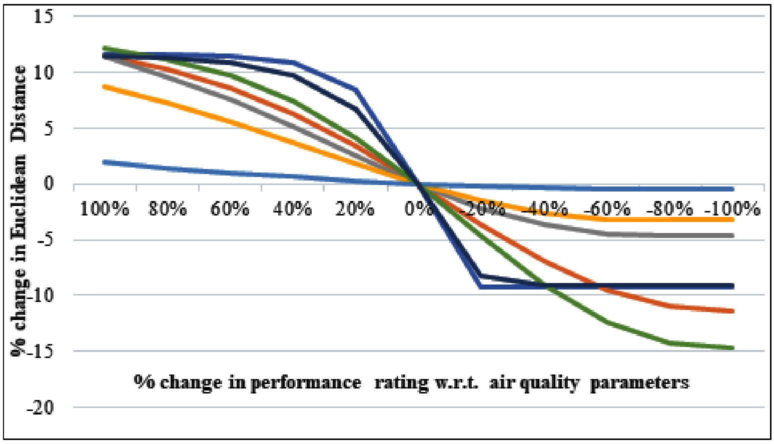


Figure 6. Sensitivity Analysis for City$_2$ 'Delhi'

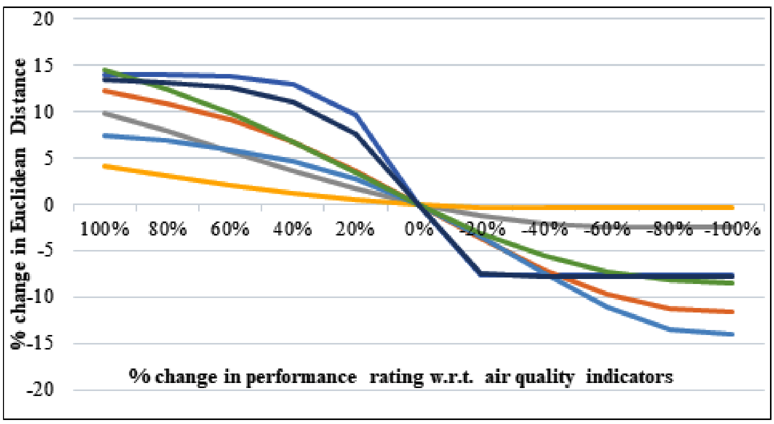


Figure 7. Sensitivity Analysis for City$_3$ 'Noida'

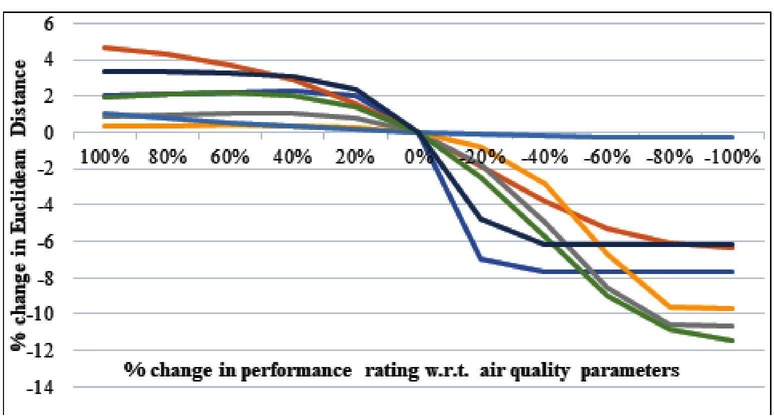


Figure 8. Sensitivity Analysis for City4 'Gurugram'

Figure 9. Sensitivity Analysis for City5 'Greater Noida'

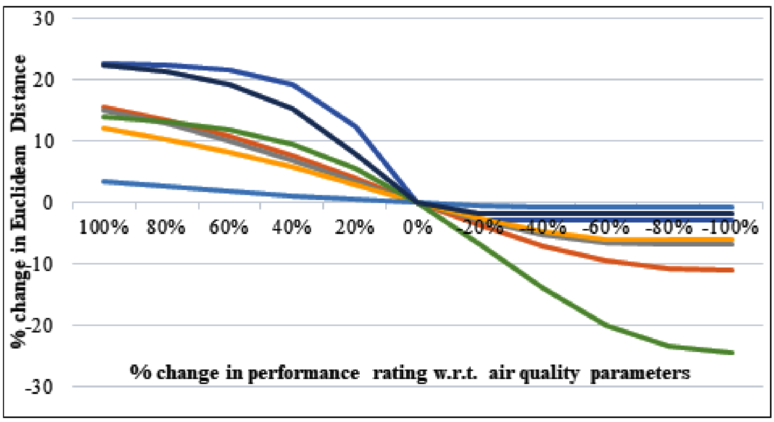


Figure 10. Sensitivity Analysis for City6 'Lucknow'

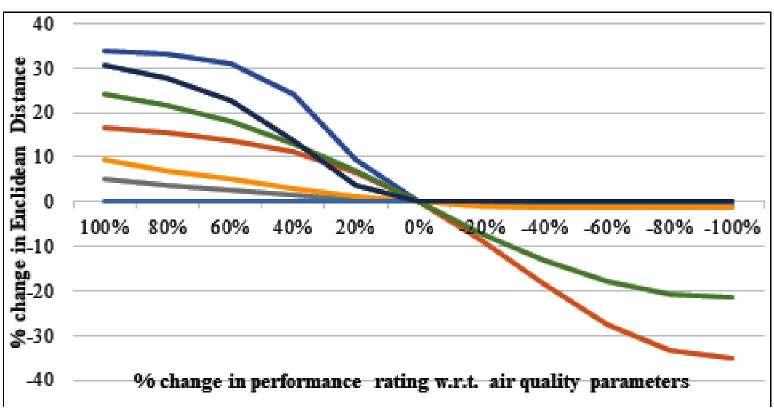


Figure 11. Sensitivity Analysis for City7 ‘Bulandshar’

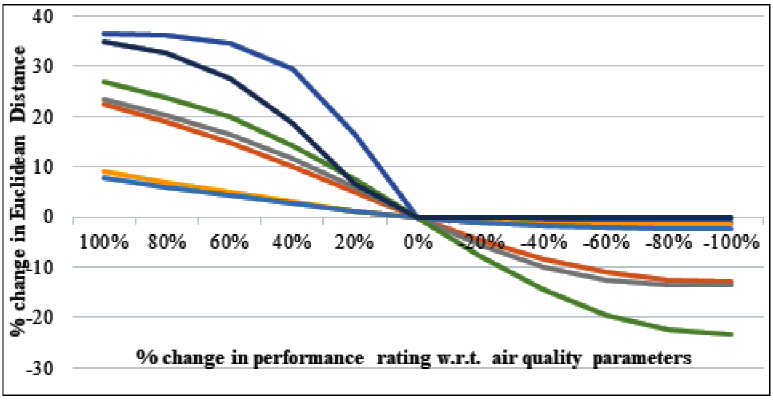


Figure 12. Sensitivity Analysis for City8 ‘Muzaffarnagar’

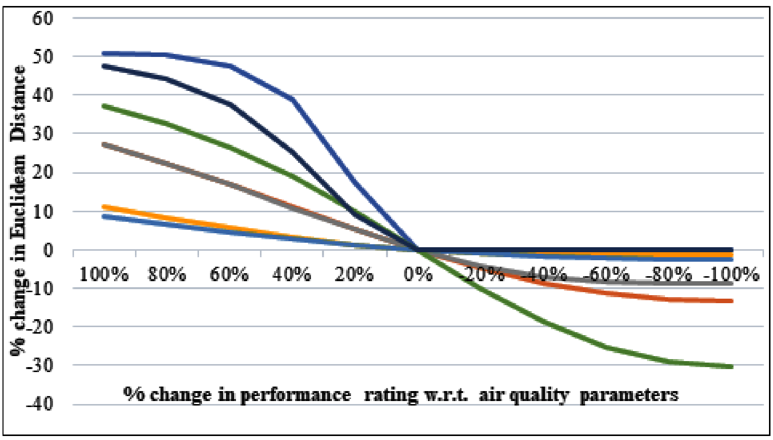


Figure 13. Sensitivity Analysis for City9 ‘Bagpat’

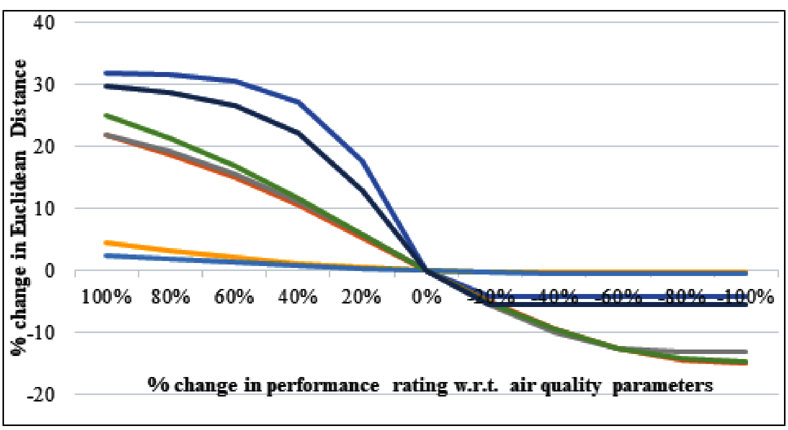


Figure 14. Sensitivity Analysis for City10 'Muzaffarpur'

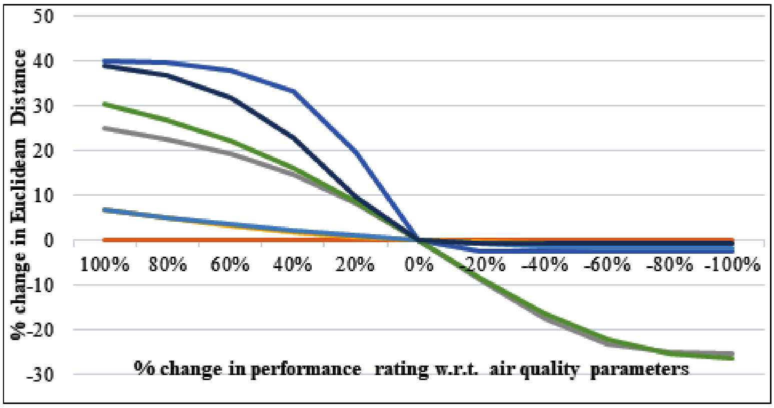


Figure 15. Sensitivity Analysis for City11 'Bhiwadi'

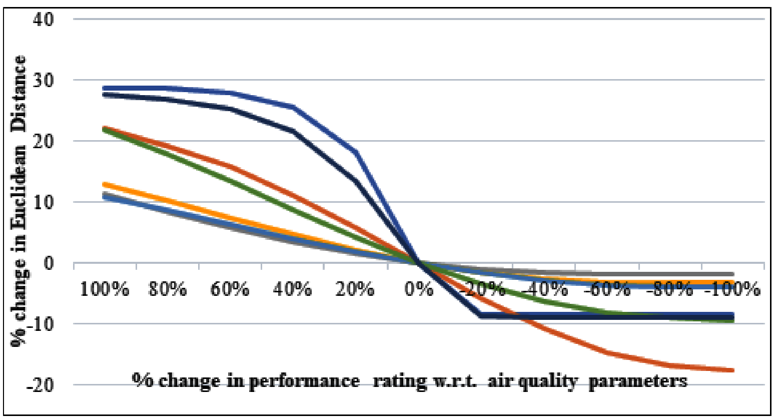


Figure 16. Sensitivity Analysis for City12 'Muradabad'

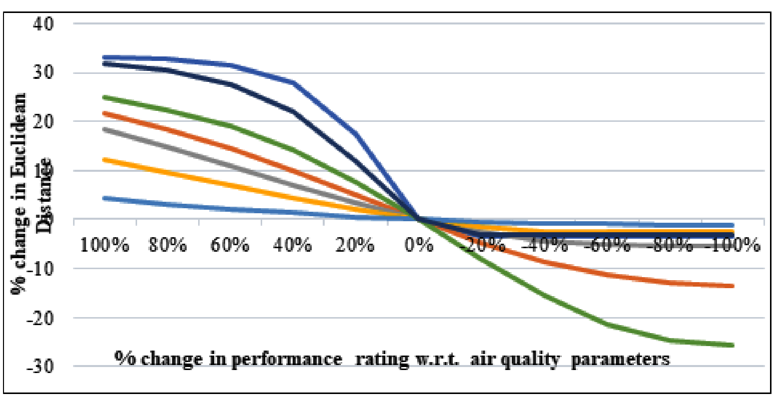


Figure 17. Sensitivity Analysis for City13 'Faridabad'

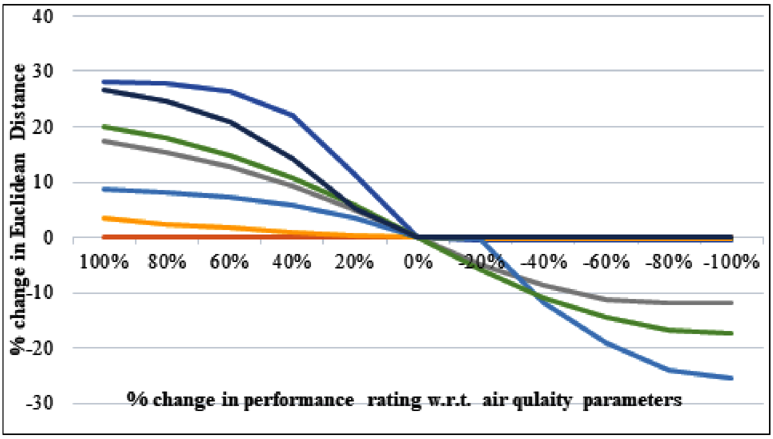


Figure 18. Sensitivity Analysis for City14 'Jind'

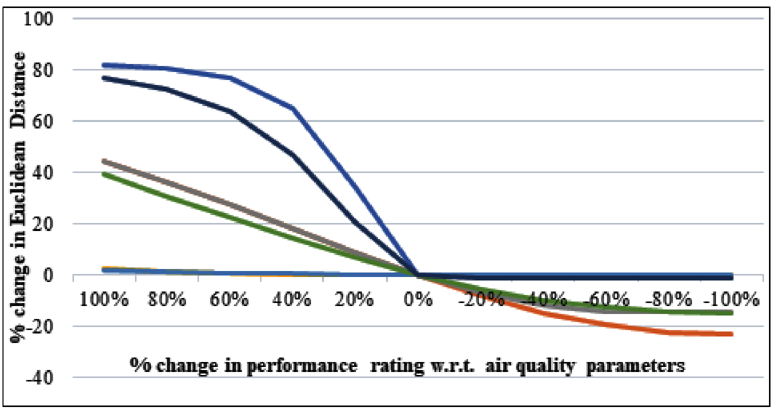
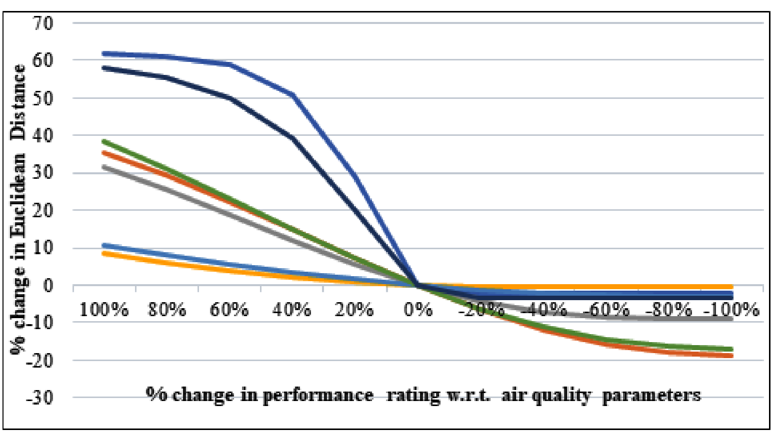


Figure 19. Sensitivity Analysis for City15 'Hisar'



i.e. 'Jind' is ranked at top position i.e. rank-1 due to having minimum Euclidean distance value as (2.682) followed by city15 i.e. 'Hissar' with ED value as (3.152) whereas city1 i.e. 'Ghaziabad' is placed at second last position (rank-14) with ED value as (6.253) followed by city3 i.e. 'Noida' with maximum ED value as (9.329). The ranking results also depict that 'Noida' is the least polluted city as compared to other fourteen Indian cities considered in the presented case study whereas 'Jind' is the highly polluted city.

Kendall's Tau test is also performed to validate the ranking results obtained by the implementation of DBA method. According to this test, any value of Kendall's coefficient nearer to +1 shows the strong positive relationship between the ranking results obtained from different MCDM methods. The Kendall's test statistics shown in table 3 depicts that the value of Kendall's coefficient for both the cases as DBA-TOPSIS and DBA-EDAS is nearer to +1. The value in both the cases is obtained as 0.67 and 0.61 respectively. However, it is observed that these coefficient values are not so nearer to +1 due to some major ranking differences between the ranking obtained from three MCDM methods as DBA, TOPSIS and EDAS. These ranking differences arise due dependency of the ranking on two different points according to the parameter's type as (i) positive ideal solution and (ii) negative ideal solution. However, in DBA, optimal point is created by considering both types of parameters (beneficiary and non-beneficiary) in a single step.

1-way sensitivity analysis is also done to check the criticality of air quality parameters for each city individually by changing the values with a percentage ranging from (-100%) to (100%). The sensitivity analysis graphs shown in figures as shown in figures (5-19) depict that the air quality parameter 'PM2.5' is the most critical parameter for most of the Indian cities considered in the presented case study except cities (1-4) whereas 'SO2' is less critical for many of the cities (1, 5-9, 11-12, 14). On the other hand, it is also observed from the sensitivity analysis that NO2, O3 and PM10 are also somehow critical for some of the cities.

Significance and Contribution of Approach

Air pollution is one of the major environmental issues that causes many serious diseases throughout the world. Every country is trying to minimize the air pollution to make the environment healthy. Various research have been conducted by many authors in this regard, but only few of them implemented the MCDM methods for the assessment of cities in any country with respect to air pollution parameters. As the MCDM methods result in the most comprehensive ranking of the alternatives i.e., cities with respect to several parameters, this ranking will surely help to the government in identifying those cities in which serious actions are highly required to control the air pollution. Although, some MCDM methods as AHP, ANP, TOPSIS, VIKOR and COPRAS have been implemented in the past, the DBA method implemented have some advantages over already existing methods as given below.

1. DBA is capable to handle beneficiary as well as non-beneficiary parameters in a single step. In DBA, the optimal point is created by considering both types of parameters. If the parameter is of beneficiary type, then the maximum value is considered as optimal and vice versa. So, there is no need to define two different solutions, i.e., one for beneficiary parameters and another for non-beneficiary parameters.
2. DBA is quite simple to implement and does not require deep knowledge of any programming language. The working of the DBA is dependent on simple matrix operations.
3. The complexity of the DBA method is less as compared to other MCDM methods.

Implications and Future Scope

The present research emphasizes on the development of a decision support system for the assessment of cities based on the air quality parameters. A decision support system is developed by implementing a well-known MCDM method i.e., DBA that provided a comprehensive ranking of cities with respect to all air quality parameters. DBA method is highly capable to solve the MCDM problems in an efficient and effective way. The major implication of this study is that the developed decision support system is demonstrated only for the cities of ‘India’. Another implication of this study is that the priority weights of the air quality parameters are taken as unity. Further, this study may be enhanced in some respects such as consideration of more air quality parameters and cities, calculation of priority weights using any other method, implementing more MCDM methods and development of any computerized decision support system using any programming language, etc.

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Rakesh Garg received the B.E., M.Tech. and the Ph.D. degree all in computer science and engineering. He is currently an Associate Professor with the Department of Computer Science and Engineering, Amity University, Noida, India. He has authored or co-authored a number of research papers in reputed international journals with various publishing houses such as IEEE, Springer, and Wiley, and guided a number of doctoral and master's degree dissertations. His major publications include articles published in the IEEE Transactions on Reliability, IEEE Transactions on Education, IEEE Transactions on Cloud Computing, IEEE Transactions on Engineering Management, Computer Applications in Engineering Education, and Journal of Multi-Criteria Decision Analysis. His research interests include component-based software engineering, software reliability, and multicriteria decision-making optimization.

Supriya Raheja is currently working as a Senior Assistant Professor in the Department of CSE & IT, School of Engineering & Technology, NCU. She has more than 10 years of extensive teaching experience at both post and undergraduate level. She is a committed researcher in the field of Operating system, fuzzy set theory and vague set theory and has completed her PhD in the same area. Her areas of interest include Procedure Oriented Programming, Object Oriented Programming, Secure Coding & vulnerabilities, Operating System, Networks and Fuzzy Set Theory. She had guided 10 M.Tech Projects and more than 25 B.Tech Projects. She has published more than 25 papers in peer reviewed reputed International Journals and in IEEE/Springer International Conferences. She is the reviewer and assistant editor of various international journals. She has done certification in Software Security from University of Maryland.