Smart Cities with Recognizance in Air Quality

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***Abstract*—The worldwide populace keeps on developing at a consistent speed, and more individuals are moving to urban communities each and every day. This led to the generation of idea of smart cities which eventually builds the sustainable environment around the world by advancing technologies which can implacably applied to understand and control various processes of the city which are subjected on water, air and energy. In current study of approach, the focus relies specifically on atmospheric pollutants which arise due to industries, factories, mining, and the combustion of fossil fuels. These activities release air pollutants that are harmful to all living things including Sulphur dioxide, nitrogen dioxide, carbon monoxide, ozone, and various others air pollutants. Additionally, it is a major risk factor for a number of health conditions, including bronchitis, lung cancer, heart problems, throat and eye disorders, asthma, skin infections, and respiratory system ailments. The aim of the current study was to conduct discrete factor analysis to analyze the factors which are responsible for degradation of the air quality. The proposed study is carried out in two phases, with the first phase measured the variation in the AQI (Air Quality Index) value of different smart cities of India for years 2015-2020, whereas in second phase we analyze the contribution of different gases such as NO2, NO, benzene, toluene, xylene, O3, CO, SO2, NOx towards the AQI value.**

Keywords— smart city; discrete factor analysis; healthcare; air Quality; air quality Index; pollutants

I. INTRODUCTION

In past times world has been chasing and discovering technology which can harness the global warming issue and benefit the future generations to come. However, we know the biggest threat to human population tends to be pollution where it evaluates in different forums. Though, World Health Organization estimates that air pollution can probably affect human lives in 1: 13 ratio every minute [1]. So, the focus is to attain the best sustainable environment for future users and provide high quality lifestyles to them.

The researchers and scientist around the globe are applying several new innovative technologies to understand the burden of everyday data which is discovered using varied tools. Certainly, these databases are having complex features so, the discrete analysis of the data is required to understand the patterns and information gathering from the data. Moreover, to develop a sustainable environment the focus relies on developing smart world around us. The concept of Smart environment comes from Smart cities where the technology advancement is implacably applied to understand and control various processes of the city.

However, current study of research focuses on concept of air pollution with ongoing smart cities development where the data has been adopted from smart cities in India and its relevance with air quality monitoring. Moreover, the major cause of air pollution was categorized in terms of harmful chemicals such as farming, industries, factories, mining, and the combustion of fossil fuels. These activities release air pollutants that are harmful to all living things including Sulphur dioxide, nitrogen dioxide, carbon monoxide, ozone, and various others air pollutants. Additionally, it is a major risk factor for a number of health conditions, including bronchitis, lung cancer, heart problems, throat and eye disorders, asthma, skin infections, and respiratory system ailments [2].

In recent years growth of urbanization becomes major focus which also led to problems with transportation, health care, air quality, and other elements of daily living. All these issues need to be addressed and for that the idea of a "smart city" was developed, and by fusing information and communication technology (ICT) with people and available resources, it can encourage sustainable growth and raise quality of life [3]. Therefore, the primary goals of creating a smart city are efficient traffic management, energy saving, waste treatment, control of pollution, and a boost in human safety and security. These all can be possible with installation of sensors at numerous locations across the city for the data collection which can further serve as a source of knowledge for resource management. So, a key characteristic of smart cities is the accessibility of data provided by sensors [4,5].

Consequently, we can see from the challenges listed above that the concept of a "smart city" perceives air quality to be a crucial element throughout the world as it is found that in many places poor air quality has become a major issue. Even according to the World Health Organization (WHO), more than seven million people die from this problem each year, and more than 80% of urban dwellers live in areas where air quality is beyond WHO guidelines [6] which indicates that there's an urgent need for preventing or minimizing the effects of air pollution otherwise it will become critical issue for the future users as well. In this context for the development of sustainable environment various steps need to be taken, among which monitoring the air of the state can be one of the preventive steps which will encourage people to carry out their everyday activities in less polluted locations. However, researchers also require to look for the task of assessing the data and providing clever answers to the problems which will help to extract knowledge from data that is buried behind it by the use of effective methods and techniques to analyze large data more effectively and efficiently.

Overcoming the above factors in the contested study, we propose to analyze the factors which are responsible for degradation of the air quality. However, to support the approach the data was quantified in accordance since 2015-2020 where the several factors in relevance to 26 smart cities of India estimated. Further, the data was synthesized to remove the irrelevant and missing values for detection of relevant patterns among the databases. Further, the analysis was conducted using SPSS (Statistical Package for the Social Sciences) and discrete factor analysis was conducted which is a potent data reduction technique where the data can be explored for different aspects that are difficult to directly quantify [7]. The results were measured in correspondence with variation in the AQI (Air Quality Index) value of different smart cities for years 2015-2020. Further, we applied factor analysis to know the contribution of different gases such as NO_2, NO, benzene, toluene, xylene, O_3, CO, SO_2, NO_x towards the AQI value as the level of air pollution increases as the AQI value rises.

The overall paper is discussed in varied sections, Section I emphasis on air pollution impacts on smart cities and discrete analysis of data by using SPSS software, however section II provides the insight of the smart cities and air pollution correlation with consistent work contributed by several authors, Section III the methodology applied for the current proposed work is discussed whereas Section IV results are outlined. Lastly, conclusion and discussion are expressed in last section.

II. PREPARE RELATED WORK

Nowadays, due to the tremendous changes in the environment, urban life is severely affected by numerous types of pollution. Among which air pollution is one of the main reasons of the sickly smart citizens. It is observed that various activities have an impact on urban air pollution such as geography, natural occurrences, meteorology, morphology, and anthropogenic [8]. Therefore, the process of managing urban air quality involves multiple functional areas, from detecting emission sources to actually removing pollutants from the atmosphere to safeguard people [9].

In relation to urban governance, smart cities are positioned as worldwide catalysts for urban resiliency, drawing interest from researchers, practitioners, and governments [10]. The advancement of SC technologies has made it easier for researchers to concentrate their efforts on enhancing resource management in smart cities. These initiatives aim to improve urban quality of life by using smart city deployed monitoring sensors. Therefore, in order to take action before an unfavorable circumstance arises, it is crucial to forecast situations in smart cities. In this context, traffic management systems are investigated for their potential to assist people and drivers enjoy city life to its fullest [11]. Additionally, a neural network model for predicting parking availability provides information on predicting parking occupancy in certain locations [12]. Another issue that has an impact on people's health is the concentration of air pollution in smart cities [13]. Consequently, an air quality monitoring and alarm system could lower the level of air pollution while taking safeguards. The literature is rich with research that provide solutions to the AQI prediction challenge. With numerous sensory devices and IoT infrastructures installed, smart cities produce abundant sources of information. This data is obtained from environments where vast amounts of data can be gathered and used by numerous smart city applications [14]. These applications span a variety of smart city models, but they all share traits like an advanced economy, advanced mobility, improved administration, evolved environment, advanced mode of living, and smart population [15]. These techniques fall under the categories of deterministic and statistical methods and include neural network approach, statistical, empirical, and physical deterministic model.

In this regard, India's smart city initiative offers a suitable framework for the governance of environmental data [16]. Although the aim is supposed to address environmental sustainability, there is a discrepancy between the plans required by the national clean air program and the services provided by smart cities [17]. Additionally, the present generation of smart cities has a limited focus on environmental services because they are driven by constructed infrastructure or technology providers [18,19].

A technique used for data analysis is exploratory factor analysis (EFA). It belongs to a class of multivariate statistical methods that search for the fewest theoretical constructs that can fully explain the covariation between a collection of measured variables. Specifically, to identify the common components that account for the configuration and organization of the measured variables [20].

III. RESEARCH METHODOLOGY

In current study of approach, we have conduct discrete factor analysis to analyze the factors which are responsible for degradation of the air quality. The aim of factor analysis is to find the underlying variables, or factors, that explain the correlational pattern between a set of observed variables. Factor analysis is frequently used to identify a few components that together explain the largest share of the variance. The proposed study is carried out in two phases, with the first phase measured the variation in the AQI (Air Quality Index) value of different smart cities of India for years 2015-2020, whereas in second phase we analyze the contribution of different gases such as NO_2, NO, benzene, toluene, xylene, O_3, CO, SO_2, NO_x towards the AQI value. The overall study is implementing using IBM® SPSS® Statistics software. It is a robust statistical software platform [7]. It is a user-friendly interface from which an organization can easily derive useful insights from data, and it is having extensive feature set.

A. Dataset Description

In proposed study of approach, we have used the dataset includes information on air quality and the AQI value at the hourly and daily levels from numerous stations located throughout various Indian cities. This dataset is available publicly on the official portal of Government of India by the *Central Pollution Control Board* [21]. The dataset consists of 26 smart cities such as Ahmedabad, Aizawl, Amaravati, Amritsar, Bengaluru, Bhopal, Brajrajnagar, Chandigarh, Chennai, Coimbatore, Delhi, Ernakulam, Gurugram, Guwahati, Hyderabad, Jaipur, Jorapokhar, Kochi, Kolkata, Lucknow, Mumbai, Patna, Shillong, Talcher, Thiruvananthapuram, Visakhapatnam [22].

B. Correlation Matrix

A correlation matrix is just a rectangular array of numbers that holds the correlation coefficients between each variable in the research and other variables. The correlation coefficient between two variables is always one. If any pair of variables in the correlation matrix has a value less than 0.5, consider eliminating one of them from the analysis.

C. KMO and Bartlett's Test

KMO stands for Kaiser-Meyer-Olkin which measures the adequacy of sample, in ranges 0 to 1, with values nearer to 1 being better and 0.6 is recommended as the absolute minimum. The correlation matrix is put to the test to see if it is an identity matrix using Bartlett's Test of Sphericity. When combined, these tests offer a minimal requirement that should be met before doing a factor analysis (or principal components analysis). The KMO range can be calculated by using summation of correlation matrix represented by r_{ij} and summation of partial covariance matrix represented by u_{ij} where i usually denotes row and j usually denotes column as shown in equation 1.

$$KMO_j = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} u_{ij}^2} \quad (1)$$

D. Communalities

Communalities are the percentage of each variable's variance that the factors can account for. In the matrix extraction values show how much of each variable's variance can be accounted for by the factors that were kept. In the common factor space, variables with high values are highly represented, whereas variables with low values are poorly represented.

E. Scree Plot

Scree plot is the visual representation of eigen value where eigen value shows how much variability that component or factor brings in the data.

IV. RESULTS

As it is well known, the availability of various sensor technologies has rapidly expanded the size of the data related to air quality [23]. However, air is one of the priceless element that is directly related to the quality of human life. It is observed that due to the ongoing release of dangerous substances such as NO_2, NO, benzene, toluene, xylene, O_3, CO, SO_2, and other particulate matter, which can have serious health effects, the air pollution has significantly increased over the past decade [24].

Consequently, in this study we analyze the different smart cities maximum AQI values using the "MAXIFS" function, whose syntax is "=MAXIFS (max range, range1, cri-teria1, [range2], [criteria2],...)," which is utilized to help determine the criteria's maximum value, where max range is the range of values used to determine maximum, range 1 is the first range to assess, criteria 1 is the criteria to use on range 1, range 2 is the second range to evaluate, criteria 2 is the criteria to use on range 2. The outcomes have been shown in Fig. 1 which shows that Ahmedabad had worst air quality index among all the 26 smart cities from the year 2015-2020.

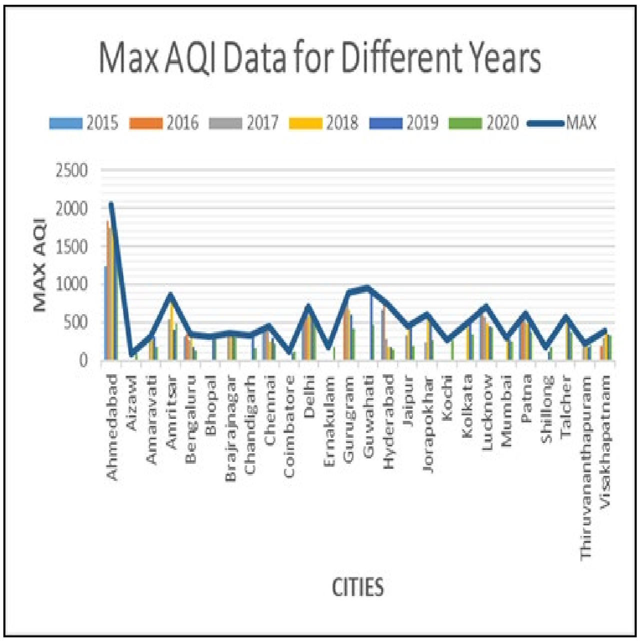

Fig. 1. The value of maximum air quality index for different years of all the smart cities.

A. Discrete Factor Analysis of different years based on AQI of various smart cities.

A table of descriptive statistics for all the variables under examination serves as the analysis's first output as shown in Fig. 2 (a). Usually, the survey's mean, standard deviation, and total number of respondents (N) are provided. Year 2016 has highest standard deviation, it means data is less stable while year 2020 has lowest standard deviation, it means data is most stable for the air quality index of different cities.

Correlation matrix shown in Fig. 2 (b) exhibits correlation between different years AQI, from the output the maximum correlation is between year 2015 and 2016, followed by year 2019 and 2020 and minimum correlation between year 2015 and 2019.

Fig. 2 (c) shows the KMO and Bartlett's test output which comes out to be 79%, it means our data met the minimum requirements.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
2015	170.81	322.868	26
2016	238.65	427.602	26
2017	296.50	389.936	26
2018	363.23	423.696	26
2019	402.19	352.835	26
2020	318.19	230.416	26

(a)

Correlation Matrix

		2015	2016	2017	2018	2019	2020
Correlation	2015	1.000	.917	.758	.643	.578	.652
	2016	.917	1.000	.896	.762	.689	.764
	2017	.758	.896	1.000	.897	.745	.822
	2018	.643	.762	.897	1.000	.816	.883
	2019	.578	.689	.745	.816	1.000	.904
	2020	.652	.764	.822	.883	.904	1.000

(b)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.796
Bartlett's Test of Sphericity	Approx. Chi-Square	191.605
	df	15
	Sig.	.000

(c)

Fig. 2. (a) Descritptive statistics matrix of different years. (b) Correlation Matrix shows correlation between different years. (c) KMO and Bartlett's test output.

In a scree plot the eigenvalue is plotted against the factor number as shown in Fig. 3. From the graph we can see that the line almost becomes flat after the third factor, indicating that each succeeding element explains a decreasing percentage of the overall variance. Also, bigger the eigen value, steeper the plot.

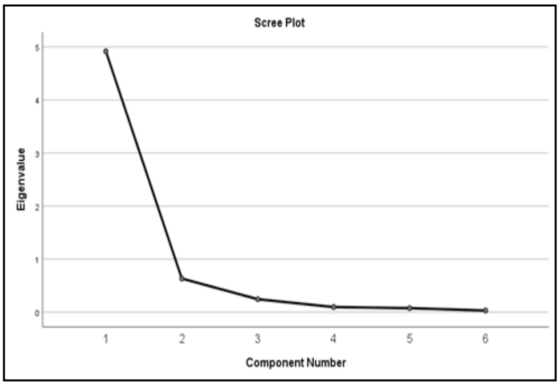

Fig. 3. Scree plot for different years.

Component matrix output is shown in Fig. 4 (a) from which it can be interpreted that there's only one factor i.e. AQI and on the basis of this one factor results are sorted for different years.

In the communalities matrix each year got different extraction value as shown in Fig. 4 (b). On the basis of the output we interpret that year 2017 represents highest AQI while year 2015 represents least the AQI.

Fig. 4 (c) shows total variance matrix, the eigenvalues are listed in the Total column. With the highest eigen value, the first component will always account for the most variation. % Variation column shows how much of the overall variance each element accounts for. The cumulative % column shows the total percentage of variation accounted for by the current and all previous components. In our output we only have one factor which is AQI.

Component Matrix[a]

	Component 1
2017	.945
2020	.927
2016	.925
2018	.924
2019	.872
2015	.834

(a)

Communalities

	Extraction
2015	.695
2016	.856
2017	.893
2018	.854
2019	.760
2020	.859

(b)

Total Variance Explained

	Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %
1	4.917	81.955	81.955

(C)

Fig. 4. (a) Component matrix for different years, (b) communalities matrix shows different extraction values for year 2015-2020, (c) total variance for component 1.

B. Discrete Factor Analysis of different gases contributing towards AQI

Fig. 5 shows the output table of descriptive statistics, we can see that NOx has maximum standard deviation and xylene has minimum standard deviation which means NOx is having least stable data while Xylene has most stable data. Fig. 6 shows that there is less variance between the variables as the graph is less steep.

Descriptive Statistics

	Mean	Std. Deviation	Analysis N	Missing N
NO	17.5747	22.78585	25949	2152
NO2	28.5607	24.47475	25946	2155
NOx	32.3091	31.64601	25346	2755
CO	2.2486	6.96288	27472	629
SO2	14.5320	18.13377	25677	2424
O3	34.4914	21.69493	25509	2592
Benzene	3.2808	15.81114	23908	4193
Toluene	8.7010	19.96916	21490	6611
Xylene	3.0701	6.32325	11422	16679

Fig. 5. Descriptive statistics matrix for different gases

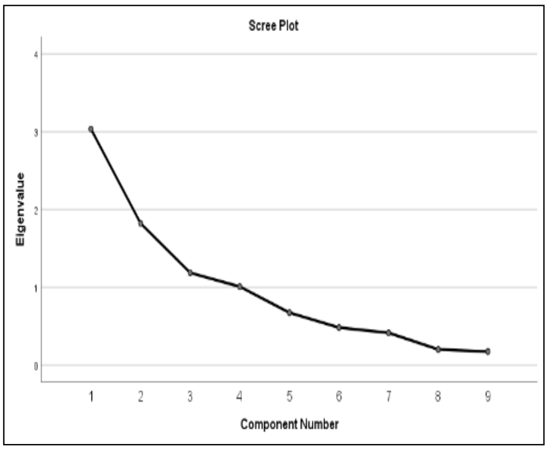

Fig. 6. Scree plot for different gases

In the component matrix table as represented in Fig. 7 (a) it is possible to see how the nine variables loaded onto the four extracted factors. The contribution of the component to the variable increases with the absolute loading value. The greater the absolute value of the loading, the greater the contribution of the component to the variable. We extracted four variables from the nine variables, dividing them into four variables based on the most essential items with identical responses in component 1 and concurrently in components 2, 3 and 4. NO2 is the first factor, benzene is second factor, SO2 is the third factor and O3 is the fourth factor. It means NO2, benzene, SO2, O3 are the four gases which are majorly responsible for high AQI.

In communalities matrix, we see the importance of every variable where greater the value, higher the importance as seen in Fig. 7 (b). from the output O3 has the highest importance compared to other gases and xylene has the least importance.

Total variance table talks about the eigen value as seen in Fig. 7 (c) The eigenvalue accurately depicts the number of extracted components, whose total should correspond to the number of items used in the factor analysis. To identify the number of components or factors expressed by a set of variables, eigenvalues larger than one must exist. Out of nine factors only 4 factors have eigen value greater than 1.

Component Matrix[a]

	Component			
	1	2	3	4
NO2	.757	-.334	.077	.187
NOx	.718	-.492	-.370	.035
NO	.645	-.475	-.453	-.054
Toluene	.637	.624	-.127	-.008
SO2	.599	-.008	.577	-.222
CO	.564	-.042	.473	-.453
Benzene	.392	.764	-.349	.014
Xylene	.468	.519	.000	.051
O3	.276	.001	.380	.844

(a)

Communalities

	Extraction
NO	.849
NO2	.725
NOx	.895
CO	.750
SO2	.741
O3	.932
Benzene	.860
Toluene	.812
Xylene	.491

(b)

	Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %
1	3.036	33.732	33.732
2	1.823	20.255	53.987
3	1.187	13.188	67.174
4	1.009	11.208	78.382

(c)

Fig. 7. (a) Component matrix for different gases, (b) communalities matrix shows different extraction values for different gases, (c) total variance for component 1,2,3, and 4.

V. CONCLUSIONS

Air is found to be essential element to keeps humans alive but as globalization takes place at rapid scale air pollution becomes one of the biggest issues in the world because air pollution poses a tremendous risk to both human health and the environment. The majority of people travel frequently in urban areas without realizing how the poor air quality is hurting their health. In this study we focus on using the AQI value to analyze trends in air quality as air quality index can provide a clear picture of the surrounding environment and the primary pollutants that are responsible for the air's quality. Therefore, understanding and monitoring the air quality is crucial to maintain our well-being and creating insight towards sustainable environment. This lead to the generation of idea of smart cities. The first step in creating sustainable smart cities is well defined data governance, which unifies fragmented data and provides integral data exchanges and their systematic interpretation for cross-sectoral decisions that are crucial for the effectiveness of environmental services in smart cities. This data governance architecture gives opportunities for developing, putting into practice, and assessing control mechanisms in real time at various sizes and industries.

The proposed study is carried out in two phases, with the first phase measured the variation in the AQI (Air Quality Index) value of different smart cities of India for years 2015-2020, whereas in second phase we analyze the contribution of different gases such as NO_2, NO, benzene, toluene, xylene, O_3, CO, SO_2, NO_x towards the AQI value. We have used SPSS software and applied discrete factor analysis on the dataset. From the output we conclude that Ahmedabad has worst air quality among 26 smart cities, and it is observed that year 2017 has highest AQI while year 2015 has least the AQI. The level of air pollution increases as the AQI value rises. Moreover, it is found that out of nine gases, majorly four gases are responsible for higher AQI value i.e. NO2, benzene, SO2, O3. Among these four gases O3 has the highest importance and xylene has the least importance in terms of AQI.

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