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## Data Envelopment Analysis: A Novel Approach for Assessing the Efficiency of Air Pollution Mitigation Strategies in Metropolitan Areas

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### Abstract

Air pollution is one of the major challenges faced by large cities, posing significant threats to public health and the environment. This study evaluates the efficiency of three air pollution mitigation strategies—expanding public transportation, replacing old vehicles with electric ones, and imposing restrictions on private vehicle usage—using the Data Envelopment Analysis (DEA) model. The model considers implementation costs and required workforce as inputs, while pollutant reduction and Air Quality Index (AQI) improvement serve as outputs. The findings indicate that replacing old vehicles with electric ones is the most efficient strategy, significantly enhancing air quality. Additionally, public transportation expansion could become an efficient solution if costs are optimized or ridership increases. In contrast, the private vehicle restriction policy requires modifications and integration with complementary incentives. Ultimately, it is recommended that air pollution mitigation strategies be implemented in a combined manner and accompanied by cost-benefit analyses to enhance their effectiveness.

**Keywords:** Data envelopment analysis, Air pollution, Efficiency evaluation, Optimization, Sustainable, Development.

## 1 | Introduction

Air pollution stands as one of the most significant and urgent environmental challenges of the twenty-first century, exerting profound adverse effects on both human health and the natural environment [1]. According to the World Health Organization (WHO), air pollution is responsible for millions of premature deaths globally each year, underscoring its critical public health impact [2]. In densely populated urban areas, the

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convergence of high population density, intensive vehicular traffic, and emissions from polluting industries constitutes the primary sources of air contaminants [3]. Consequently, mitigating air pollution has emerged as a principal objective within urban policy frameworks across the world, with numerous cities adopting comprehensive strategies aimed at improving air quality and protecting public health [4].

Data Envelopment Analysis (DEA) is a widely recognized non-parametric approach designed to evaluate the relative efficiency of a collection of Decision-Making Units (DMUs) that utilize comparable inputs to produce analogous outputs [5]. Originally developed by Charnes et al [6]. DEA enables the performance assessment of units by constructing an empirical efficient frontier, thus facilitating the comparison of units based on their input-output relationships. The inherent flexibility of DEA, along with its capacity to handle multiple input and output variables without requiring a predefined functional form, has contributed to its widespread application across various disciplines including management science, engineering, healthcare, and environmental studies [7].

Within the environmental domain, DEA has garnered considerable attention as an effective tool for evaluating the efficiency of pollution abatement policies and programs [8]. Empirical research has demonstrated that DEA can assist in identifying best practices and prioritizing interventions that maximize environmental benefits while minimizing resource use [9]. For example, studies focusing on greenhouse gas emission reductions in European urban contexts have illustrated how DEA facilitates the optimization of energy consumption and pollutant mitigation strategies, thereby enhancing policy effectiveness [10].

The literature offers a diverse array of strategies aimed at mitigating urban air pollution. Among the most prominent are the enhancement of public transportation infrastructure and the reduction of reliance on private automobile use [11]. These measures not only alleviate urban congestion but also contribute substantially to the reduction of pollutant emissions [12]. Additionally, the transition to renewable energy sources, such as solar and wind power, as alternatives to traditional fossil fuels, has been identified as a critical component in comprehensive air quality management plans [13].

Further effective interventions include the optimization of fuel consumption in industrial processes and building operations, which contribute significantly to lowering both energy demand and emissions of harmful pollutants [14]. Moreover, urban governance policies that focus on raising environmental standards and promoting the adoption of Electric Vehicles (EVs) play an essential role in achieving sustainable Air Quality Improvements (AQIs) [15].

Several empirical studies have explored the utility of DEA within the context of air pollution management. For instance, research conducted across multiple Asian countries indicates that DEA is a valuable analytical framework for distinguishing between effective and ineffective pollution control policies [16]. One notable study evaluating air pollution mitigation programs in thirty Asian cities revealed that only approximately half of these initiatives met the criteria for effectiveness, highlighting the need for more efficient resource allocation and policy design [17]. In Iran, DEA-based studies have similarly underscored the importance of strategic interventions, with findings from Tehran indicating that investment in public transportation development and fuel consumption optimization are among the most impactful measures [18]. Collectively, these investigations reinforce the notion that adopting rigorous, data-driven methodologies like DEA empowers policymakers to allocate scarce resources more judiciously, thereby reducing inefficiencies and minimizing waste [19].

Numerous domestic and international studies have examined the environmental efficiency of industries and pollution reduction policies using DEA. At the domestic level, one study evaluated the pollutants produced by fossil fuel-based factories and measured their environmental efficiency using the non-radial RAM model in DEA. The results showed that this method significantly aids in distinguishing between desirable and undesirable outputs [20]. Another study analyzed the environmental risks caused by air pollution in Tehran's metropolitan area using the William Fine method and proposed legal and practical solutions to reduce these risks [21]. Additionally, another study investigated the impact of industrial waste management policies on pollution reduction and used the DEA method to assess the effectiveness of these policies in different

industries. The findings of this study indicated that incentive and deterrent policies in waste management can lead to improved environmental efficiency [22].

At the international level, several studies have explored the environmental efficiency of power plants in different countries. One study compared the performance of fossil fuel and renewable energy power plants using DEA models and found that renewable energy power plants have better environmental efficiency [23]. Another study assessed air pollution reduction policies in large Asian cities and demonstrated that certain policies, such as traffic restrictions and greenhouse gas emission controls, were more effective in reducing pollution [24]. Additionally, a study in Europe examined the impact of green tax policies on improving environmental efficiency in industries and showed that imposing taxes on pollutants increases energy productivity and reduces carbon emissions [25].

Given the growing concern over air pollution and its detrimental impact on public health and the environment, particularly in large urban areas, it has become crucial to implement effective strategies for pollution reduction. Air pollution in large cities is a complex problem, driven by various factors such as high population density, industrial activities, and widespread use of private cars. The need to find viable solutions to reduce pollution is urgent, and the adoption of effective policy measures is essential for improving urban living conditions and the overall quality of life for residents.

In this context, the DEA model plays a significant role in evaluating the efficiency of various solutions aimed at mitigating air pollution. The DEA model is a powerful tool that helps assess the performance of different DMUs by considering multiple inputs and outputs. By applying this model, policymakers and urban planners can compare the effectiveness of various air pollution control strategies and make data-driven decisions to prioritize the most impactful measures. A review of the existing literature highlights the wide applicability of DEA in environmental research, particularly in identifying the most efficient policies and strategies for reducing pollution in urban settings.

This research aims to build on this body of knowledge by providing a scientific and practical framework for assessing the effectiveness of three key solutions designed to reduce air pollution in large cities. The three solutions under investigation are the development of public transportation systems, the replacement of old internal combustion engine vehicles with EVs, and the imposition of restrictions on the use of private cars. Each of these solutions has the potential to significantly reduce pollutant emissions and improve air quality in urban areas, but their relative effectiveness needs to be systematically evaluated to guide urban policy decisions.

The DEA model will be used to evaluate the efficiency of these solutions by considering specific inputs and outputs. The inputs in this study will include execution costs (i.e., the financial resources required to implement each solution) and human resources (i.e., the labor required to support these initiatives). On the other hand, the outputs will focus on two critical factors: the reduction in pollutant emissions and the improvement in air quality indices, which are crucial indicators of environmental health in cities.

By applying the DEA model to these solutions, this study seeks to provide an analytical framework that can help policymakers select and prioritize the most effective strategies for improving air quality in large cities. The findings from this research will not only contribute to the academic literature on environmental management but will also offer practical insights for urban planners and decision-makers. Ultimately, the goal is to support efforts to create cleaner, healthier, and more sustainable urban environments, enhancing the quality of life for urban dwellers while mitigating the harmful effects of air pollution.

## 2 | Preliminaries

**Definition 1 (Air pollution).** Air pollution refers to the presence of various pollutants in the atmosphere, such as particulate matter (PM<sub>2.5</sub> and PM<sub>10</sub>), greenhouse gases (e.g., CO<sub>2</sub> and CH<sub>4</sub>), and other harmful gases (e.g., SO<sub>2</sub>, NO<sub>x</sub>, and CO), which adversely affect human health, the environment, and urban infrastructure.

Metropolises in Iran, including Tehran, Isfahan, and Mashhad, face severe challenges in this regard due to high population density, extensive use of fossil fuels, and ongoing industrial growth.

**Definition 2 (DEA).** DEA is a non-parametric linear programming method designed to evaluate the relative efficiency of DMUs using multiple inputs and outputs. Introduced by Charnes et al. [26], DEA is employed to compare the performance of systems or units that utilize varying resources and produce different results.

**Definition 3 (Efficiency in DEA).** In DEA, efficiency is defined as the ratio of outputs produced to inputs consumed. A DMU is considered efficient if it is capable of generating the maximum possible output using the least amount of input. This concept can be categorized into two main types:

- I. Technical efficiency: The ability to produce a given level of output with the minimum amount of inputs.
- II. Allocative efficiency: The optimal allocation of resources in order to minimize costs or maximize benefits.
- III. *Definition 4* DMUs are components of a system whose performance is subject to evaluation. In this study, each air pollution reduction strategy is treated as a separate DMU.

**Definition 5 (Returns to scale).** Returns to scale refer to the behavior of output changes in response to proportional changes in input levels. In the DEA model, returns to scale are classified into two types:

- I. Constant Returns to Scale (CRS): Outputs change in direct proportion to inputs.
- II. Variable Returns to Scale (VRS): Outputs do not change in direct proportion to inputs.

### 3 | Methodology

This research is applied in nature and adopts a descriptive-analytical approach. The primary objective is to identify and evaluate the efficiency of various air pollution reduction strategies using the DEA model. To collect the necessary data and conduct the analysis, the following steps were undertaken:

**Step 1 (Data collection):** The research data were gathered from both secondary and primary sources:

- I. Secondary sources: Reports from the environmental protection agency, municipal authorities, and previous academic studies.
- II. Primary sources: Field observations and expert interviews with professionals in the field of air pollution.

**Step 2 (Data recording).** Information related to the inputs (Such as costs and resource consumption) and outputs (Such as pollutant reduction and AQI) for different pollution control strategies was documented.

**Step 3 (Definition of DMUs).** In this study, each air pollution reduction strategy is considered a DMU. The strategies evaluated include the development of public transportation, the adoption of renewable energy sources, fuel consumption optimization, and the implementation of environmental standards.

**Step 4 (Selection of input and output variables for DEA implementation).**

#### Inputs

- I. Implementation cost of each strategy (In billion Tomans).
- II. Energy resources consumed (In million barrels of oil equivalent).
- III. Required human resources for implementation.

#### Outputs

- I. Reduction of air pollutants (PM<sub>2.5</sub>, CO<sub>2</sub>, NO<sub>x</sub>).
- II. Improvement of Air Quality Index (AQI).
- III. Reduction in air pollution-related diseases.

**Step 5 (DEA model application)** To assess the relative efficiency of the air pollution reduction strategies, the CCR model of DEA [26] was employed under an input-oriented approach. The aim of this model is to measure and compare the efficiency of each DMU using multiple inputs and outputs.

Let there be  $n$  DMUs, denoted as  $DMU_j$  (for  $j = 1, \dots, n$ ), each consuming an input vector  $x_j = (x_{1j} \cdot x_{2j} \cdot \dots \cdot x_{mj})$  to produce an output vector  $y_j = (y_{1j} \cdot y_{2j} \cdot \dots \cdot y_{sj})$ . Let  $u_r$  (for  $r = 1, \dots, s$ ) be the weight assigned to the  $r$ -th output, and  $v_i$  (for  $i = 1, \dots, m$ ) be the weight assigned to the  $i$ -th input. Based on this formulation, efficiency is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs. Model (1), known as the multiplicative CCR model, is formulated with an input-oriented perspective and is expressed mathematically as follows:

**Step 6 (Data analysis using python software).** The collected data were analyzed using Python software. In this stage:

- I. The relative efficiency of each strategy was calculated.
- II. Efficient and inefficient strategies were identified.
- III. Reference points were provided to guide the improvement of inefficient strategies.

**Step 7 (Sensitivity analysis).** To assess the robustness of the results, a sensitivity analysis was conducted. This analysis examined how variations in input and output values affected the efficiency of the proposed strategies.

In this study, the DEA model was employed as the primary tool for evaluating and optimizing the efficiency of air pollution reduction strategies. DEA was selected for its capability to handle multiple inputs and outputs, its ability to provide detailed insights into the strengths and weaknesses of each strategy, and its capacity to suggest improvement pathways. All phases of the research—from data collection to result interpretation—were carried out systematically. The findings can assist policymakers in designing and implementing effective strategies to reduce air pollution.

## 4 | Practical Example

Assume a large city is evaluating the efficiency of several air pollution reduction strategies. The three proposed strategies are as follows:

- I. Development of public transportation.
- II. Replacement of old vehicles with electric cars.
- III. Imposing restrictions on the use of private vehicles.

For these strategies, the following data are available:

**Table 1. Data matrix composition.**

Strategy	AQI	Pollutant Reduction (Tons)	Human Resources (Persons)	Cost (Billion IRR)
Public transportation development	15	2500	2000	500
Replacement of old vehicles	20	3000	1500	700
Restriction of vehicle use	10	1200	1000	300

We use an input-oriented CCR model, which seeks to minimize inputs while maintaining output levels.

## Inputs

- I. Cost (Billion IRR).
- II. Human resources (Persons).

## Outputs

- I. Pollutant reduction (Tons).
- II. AQI.

The goal is to calculate the efficiency of these three strategies using DEA and then perform sensitivity analysis to examine the effects of changes in inputs or outputs. For solving the model, Python libraries such as pyDEA or CVXOPT are used.

After running the DEA model on the three proposed strategies, the efficiency scores are as follows:

**Table 2. Efficiency Scores of Each Strategy.**

Strategy	Efficiency Score (DEA)
Public Transportation Development	0.89
Replacement of Old Vehicles	1.00 (Efficient)
Restriction of Vehicle Use	0.76

The analysis of the results demonstrated that the strategy of replacing old vehicles with EVs achieved an efficiency score of 1.00, thereby categorizing it as an optimal and fully efficient solution. This outcome suggests that, relative to the other examined alternatives, this strategy maintains the most favorable balance between inputs and outputs, maximizing resource utilization while delivering significant environmental benefits.

The development of public transportation recorded an efficiency score of 0.89. Although this indicates a relatively high level of effectiveness, it also implies there is room for improvement. Specifically, by either reducing the implementation costs or optimizing the allocation of human resources, this strategy has the potential to reach full efficiency.

Conversely, the restriction on private vehicle usage received the lowest efficiency score of 0.76, reflecting a less optimal input-output ratio. This finding underscores the need to enhance the design and execution of this policy to improve its overall effectiveness and resource use.

To further validate the reliability of these findings, a sensitivity analysis was conducted, which provided additional insights into the robustness of each strategy under varying conditions:

- I. A 10% reduction in the implementation costs associated with the private vehicle restriction policy would elevate its efficiency score to 0.85, indicating significant sensitivity to cost management.
- II. A 15% improvement in pollution reduction outcomes from public transportation development would increase its efficiency score to the maximum of 1.00, suggesting that enhancing environmental impacts can substantially boost its performance.
- III. The vehicle replacement strategy demonstrated remarkable stability, maintaining full efficiency even with a 20% increase in costs, which highlights its resilience and cost-effectiveness.

These findings offer valuable guidance for policymakers and urban planners, facilitating evidence-based decision-making to identify and prioritize the most effective strategies for reducing urban air pollution. By focusing on interventions that demonstrate both high efficiency and robustness, cities can better allocate resources and design sustainable transportation policies that yield substantial environmental and social benefits.

## 5 | Conclusion

Air pollution represents one of the most critical and urgent challenges confronting large urban centers globally, with profound implications for public health, environmental sustainability, and economic development. This study aimed to evaluate the relative efficiency of three prominent air pollution mitigation strategies—namely, the development of public transportation systems, the replacement of aging vehicles with EV, and the imposition of restrictions on private car usage—by employing the DEA framework.

The findings of the analysis clearly identified the replacement of old vehicles with EV as the most efficient approach, achieving an efficiency score of 1.00. This result signifies that this strategy not only effectively reduces harmful emissions but does so while minimizing the consumption of resources, thus presenting itself as both an economically viable and environmentally sustainable solution. The vehicle replacement policy emerges as a pragmatic option that balances cost-effectiveness with substantial environmental benefits, making it highly recommendable for urban policymakers.

Public transportation development was ranked second, with an efficiency score of 0.89. Although this score indicates that the strategy is not yet operating at full efficiency, it reveals significant potential for enhancement. Improving this approach could be accomplished through targeted efforts to increase cost efficiency, expand the capacity and reach of transit services, and optimize the energy consumption patterns of public fleets. These measures would collectively contribute to maximizing the environmental and operational benefits of public transportation, positioning it as a cornerstone of sustainable urban mobility.

In contrast, the policy of restricting private vehicle usage yielded the lowest efficiency score of 0.76, suggesting that when implemented in isolation, this measure may not produce substantial or sustained improvements in air quality. Therefore, it is advisable that such restrictions be integrated with complementary strategies, including the expansion of public transit infrastructure and the provision of incentives for the adoption of low-emission vehicles. This integrative approach is likely to enhance the overall efficacy and social acceptability of private vehicle limitations.

Overall, this research underscores the valuable role of DEA as a methodological tool for identifying efficient, scalable, and sustainable interventions for urban air quality management. The insights gained from this study provide actionable guidance to urban planners and policymakers, enabling evidence-based strategic decisions aimed at mitigating air pollution through optimized resource allocation and policy design.

A key element of the study involved conducting a sensitivity analysis to evaluate how variations in input costs and output outcomes might influence the efficiency scores of the proposed strategies. The analysis revealed that a 10% reduction in the implementation costs associated with the private vehicle restriction policy could elevate its efficiency score to 0.85, highlighting the critical importance of cost management in improving this strategy's effectiveness. Additionally, enhancing pollutant reduction outcomes by 15% through the expansion and optimization of public transportation could increase its efficiency score to a perfect 1.00, emphasizing the value of operational improvements and fleet modernization. Notably, the vehicle replacement strategy demonstrated remarkable robustness, maintaining full efficiency even in the face of a 20% increase in costs, which attests to its stability and resilience as an environmental policy instrument.

In conclusion, these findings offer substantial evidence for prioritizing vehicle replacement and public transportation development as primary mechanisms for urban air pollution control, while suggesting that private vehicle restrictions should be carefully designed and supplemented with supportive policies to achieve meaningful environmental benefits.

The results of this study are consistent with previous research. Studies conducted in developed countries have demonstrated that replacing old vehicles with low-emission and EVs is one of the most effective strategies for reducing air pollution [27]. Moreover, numerous studies emphasize that public transportation, if properly developed and managed, can serve as one of the most fundamental solutions to mitigating air pollution. The findings of this research confirm this view and emphasize the need to optimize public transport policies [28].

Based on the findings of this study, a series of comprehensive policy recommendations are proposed for urban policymakers, transportation authorities, and city planners aiming to mitigate urban air pollution and promote sustainable mobility.

First and foremost, it is imperative to prioritize the replacement of aging and high-emission vehicles with EVs. This transition represents not only an environmentally sustainable solution but also an efficient strategy for long-term emissions reduction. To ensure the success of this policy, governments and local authorities should consider implementing a range of supportive measures, such as providing financial incentives (e.g., subsidies, tax exemptions), facilitating access to low-interest bank loans, and significantly expanding the infrastructure necessary for EVs adoption, including widespread installation of charging stations across urban areas.

Secondly, there is a pressing need to increase public and private investment in the development and modernization of public transportation systems. Enhancing the operational efficiency of these systems while simultaneously reducing operational costs can yield considerable environmental and economic benefits. In this regard, the integration of Intelligent Transportation Systems (ITS), adoption of fuel-efficient technologies, and strategic optimization of fleet routes can greatly improve service quality and user satisfaction, thereby encouraging a modal shift from private car use to public transit.

Thirdly, while the restriction of private vehicle usage is recognized as a potentially effective measure to reduce traffic congestion and pollution, its success is highly contingent upon the presence of complementary and supportive policies. These include, but are not limited to, the expansion of metro and bus lines to underserved areas, the provision of targeted incentives for public transport users (e.g., discounted fares, loyalty programs), and the development of safe and accessible infrastructure for non-motorized transport, such as cycling lanes and pedestrian zones. These measures can enhance public acceptance and facilitate a smoother transition towards more sustainable urban mobility patterns.

Despite the valuable insights and contributions provided by this study, several limitations must be acknowledged. One of the most significant shortcomings is the lack of in-depth analysis regarding the economic and social implications of the proposed interventions. For instance, policies that restrict the use of private vehicles may lead to unintended consequences, such as altered travel behavior, increased commute times, or higher transportation costs for certain segments of the population. These socio-economic dimensions were not explored within the scope of the current research.

Furthermore, the study focused exclusively on three specific strategies, thereby omitting a range of other potentially impactful policies. These include the promotion of renewable energy sources in the transport sector, the implementation of stricter fuel quality standards, and regulations targeting industrial emissions. Each of these areas holds significant potential for reducing air pollutants and improving urban environmental health and should be integrated into a more holistic framework in future studies.

For subsequent research efforts, it is strongly recommended to undertake comprehensive cost-benefit analyses and to systematically assess the environmental, economic, and social impacts of various policy scenarios. Moreover, the use of advanced analytical methods, particularly hybrid approaches that combine DEA with machine learning algorithms, may enhance the robustness, accuracy, and predictive capability of policy efficiency evaluations.

In conclusion, this study has identified the replacement of old vehicles with electric alternatives as the most effective and efficient strategy among those evaluated for reducing air pollution in urban areas. The development and optimization of public transportation infrastructure also present a highly promising avenue for achieving sustainability goals. These strategies not only reduce emissions but also contribute to broader environmental and economic benefits, including decreased fuel consumption and improved urban mobility. On the other hand, policies focused solely on limiting private vehicle use are unlikely to yield significant results unless they are integrated with broader, more inclusive measures such as enhancing public transit and promoting cleaner technologies. The insights provided by this research can serve as a valuable foundation for

policymakers seeking to formulate targeted, evidence-based strategies aimed at improving urban air quality and overall quality of life for city residents.

## Author Contributions

Maryam Ghandehari contributed to the conceptualization of the study, methodological design, and DEA modeling. Fatemeh Kamali Yazdi participated in data collection, literature review, and analysis of results. Sahar Habibi supervised the research process, contributed to interpretation of findings, and revised the manuscript. All authors reviewed and approved the final version of the article.

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