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Assessment of Commute-Related Emission Reduction Scenarios for Administrative Services

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ABSTRACT

Mobile sources from administrative service commutes significantly contribute to air pollutant emissions in metropolises, underscoring the need for travel demand management (TDM) and referral reduction strategies. A software-oriented approach is crucial in metropolises like Karaj due to the high commuting volume. Evaluating pollutant emissions across scenarios offers insights for effective air pollution reduction strategies. Scenarios aim to assess air pollution management, considering software and hardware aspects. Data collection involved field interviews and questionnaires for individuals commuting to administrative offices. These challenges and considerations informed the classification of the studied vehicle fleet based on system types, production years, emission standards, fuel types, and vehicle classes. We designed scenarios to minimize standard pollutants by reducing in-person visits to administrative offices and replacing the fleet with hybrid and natural gas vehicles. Results were compared with the baseline scenario, computing emissions using the International Vehicle Emission Model (IVE). The comparative analysis highlighted that substantial pollutant reduction comes from combined commuting reduction and a decrease in referral numbers. TDM emerged as the most cost-effective strategy, executed with principled planning. In conclusion, this study's scenario exploration provides insights for policymakers and urban planners. Adopting a software-oriented approach to mitigate air pollutant emissions through commute reduction and strategic TDM can significantly enhance air quality and curb traffic-related pollution in cities like Karaj.

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INTRODUCTION

Increasing urbanization has raised significant air pollution concerns in big cities and developing nations, exacerbated by a substantial urban population (58% in 2018) projected to reach 68% by 2050 (Klohe et al., 2021; Vafa-Arani et al., 2014). The use of fossil fuels, as the primary source of energy in transport worldwide, aggravates this situation since their combustion is the cause of several pollutants, mainly carbon monoxide (CO), sulfur oxides (SO_x), particulate matter (PM), volatile organic compounds (VOC_s), greenhouse gases such as carbon dioxide (CO_2), methane (CH_4), nitrogen dioxide (NO_2) among others, making it a significant factor in climate change and environmental degradation (Abdelzaher, 2022; Viteri et al., 2023).

The primary sources of air pollutants can be broadly categorized into two main groups: mobile and stationary sources, so mobile sources are one of the main sources of air pollutants (Shahbazi et al., 2022; Upadhya et al., 2024). Addressing this involves replacing old vehicles (hardware section) and implementing travel demand management (TDM) strategies (software

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section), prioritizing cost-effectiveness, although software aspects have been less emphasized (Siddiqi & Buliung, 2013).

Commuting stands out as the primary and rapidly growing source of air pollutants, serving various purposes, including administrative services, resulting in significant traffic (Kissinger & Reznik, 2019; Moeinaddini et al., 2017). In Iran, a developing country, increasing transportation time, fuel consumption, vehicle numbers, and TDM issues in major urban centers exacerbate the situation (Shokohian & Qazi Nejad, 2010).

Diverse strategies and policies have been implemented to enhance air quality and diminish air pollutants to control vehicle-related emissions. These include promoting public transportation, upgrading fuel quality, adopting emission-compliant hybrid vehicles, fleet replacement, and implementing lead-free and low-sulfur petrol (Liu et al., 2020; Velázquez et al., 2023). An integral solution involves transportation systems management and TDM techniques, which revolve around two primary policies: 1) limiting private car use and 2) encouraging public transportation utilization (Fallah Tabati et al., 2018). The main objective underlying these policies is to reduce travel demand while decreasing the need to travel. This is realized through various approaches, including telecommuting, electronic services, service distribution within the city, and TDM during peak hours (achieved by modifying working hours, adjusting public transportation frequencies on specific routes, and employing intelligent transportation systems) (Batur & Koç, 2017). In TDM, it's crucial to consider travel purposes and vehicle types, offering various alternatives to reduce travel demand and decrease private car usage in transportation fleets. (Maleki, 2018).

Given the significance of economic, environmental, and renewable resource factors, emission measurement methods are vital. However, direct measurement, due to its costliness, is often replaced by estimation (Abdelzaher et al., 2018; Elkhouly et al., 2021). The International Vehicle Emissions (IVE) software, developed with US Environmental Protection Agency support in 2007, offers a tailored solution for estimating air pollutant emissions from fuel usage, particularly beneficial for developing countries, and outperforms alternatives like COPERT and MOBILE (Patiño-Aroca et al., 2022).

As a result, the IVE model was developed to estimate vehicle emissions globally, emphasizing developing nations, with the primary goal of offering an efficient and reliable methodology for managing such data (Viteri et al., 2023).

This study addresses the urgent need to reduce air pollutant emissions during administrative commutes, particularly in cities like Karaj, where commuting is a significant pollution source. It sets three objectives: 1) The primary objective is to use the IVE model to address atmospheric emissions from mobile sources, particularly in developed areas like Karaj. 2) Investigating the benefits of natural gas and hybrid vehicles in Karaj to tackle environmental challenges and increased fossil fuel use. 3) Another important objective includes evaluating the potential reduction in referrals to administrative services, with the strategic goal of minimizing commute and aligning with the broader goal of optimizing administrative processes to reduce overall travel in the form of TDM.

This research uniquely focuses on Travel Demand Management (TDM), commuting, and administrative services using the IVE model, examining their interplay with environmental concerns. It proposes smart city solutions to reduce costs and unnecessary visits to administrative centers by improving citizen facilities and services.

MATERIAL AND METHODS

Study of area

Karaj, the capital of Alborz province, has a population of 2,512,737 (2015) and is located east of the province. The city witnesses approximately 3,000,000 daily commuting trips, accommodating about 364,000 passengers (excluding drivers). Daily vehicular trips in the city and suburbs total 1.6 million and 0.3 million, respectively (Karaj, 2014).

Field survey

A survey was conducted from February to May 2022 using both in-person and online questionnaires due to the pandemic. 250 questionnaires were administered in person, and an additional 250 were completed online by individuals accessing administrative services centers in Karaj. The questionnaire covered personal information, vehicle usage, and suggestions for reducing referrals to administrative centers. The statistical population comprised 36% women and 64% men, with only 13% using public transportation for their commute, and the average travel distance was 15 minutes. Participants recommended prioritizing city-wide public transportation, implementing intelligent services, and establishing cyclist-friendly paths to improve air quality and alleviate traffic congestion.

Emission estimation

The data related to road vehicles encompasses factors such as vehicle count, vehicle type, age, fuel, and emission control technologies (Gao et al., 2020a). This study focuses on mobile fleet sources related to administrative services, collected from commuting referrals accessing administrative offices. It utilizes the IVE model, considering engine technology, emission control devices, driving behaviors, and vehicle emission factors to compute vehicle emissions (Wang et al., 2008).

Vehicle Fleet Composition

The study of vehicle technologies is one of the most pivotal aspects of vehicle emissions analysis (Wang et al., 2008). The field study data concerning driving behaviors is essential to accurately estimating vehicle emissions, and it should be considered in the total vehicle emission classification as these emissions are significantly influenced by driving behaviors (Fu et al., 2013). Furthermore, for power calculation using GPS data and Google Maps, second-by-second speed, height, and distance values were collected for different vehicle categories across various road types and times of day, with a priority on peak traffic hours to achieve comprehensive representation (Viteri et al., 2023). The collected GPS data, which represents actual driving behaviors, was integrated into emission prediction models like IVE, along with local temperature and humidity data (Pathak et al., 2016). The methodology aims to capture accurate power calculations for emissions assessment. In the IVE model, the Variable Specific Power (VSP) was adapted as a pivotal power-related parameter closely related to emissions production. The calculation methodology for VSP is shown in equation (1) (Outapa et al., 2017).

$$VSP = V * \left[1.1a + 9.81\left(\operatorname{atan}\left(\sin\left(grade\right)\right)\right) + 0.132\right] + 0.000302v^3 \tag{1}$$

Where v is the vehicle velocity, a is the vehicle acceleration, and grade is the road slope. The following equations (2, 3, and 4) show how to estimate engine stress (Hao et al., 2015; Shahbazi et al., 2016):

$$Engine\,Stress = RPM\ Index + \left(0.08\frac{ton}{KW}\right) * Preave\,Power \tag{2}$$

$$Preave\,Power = Average\left(VSP\right)\left(\frac{KW}{ton)}\right) \tag{3}$$

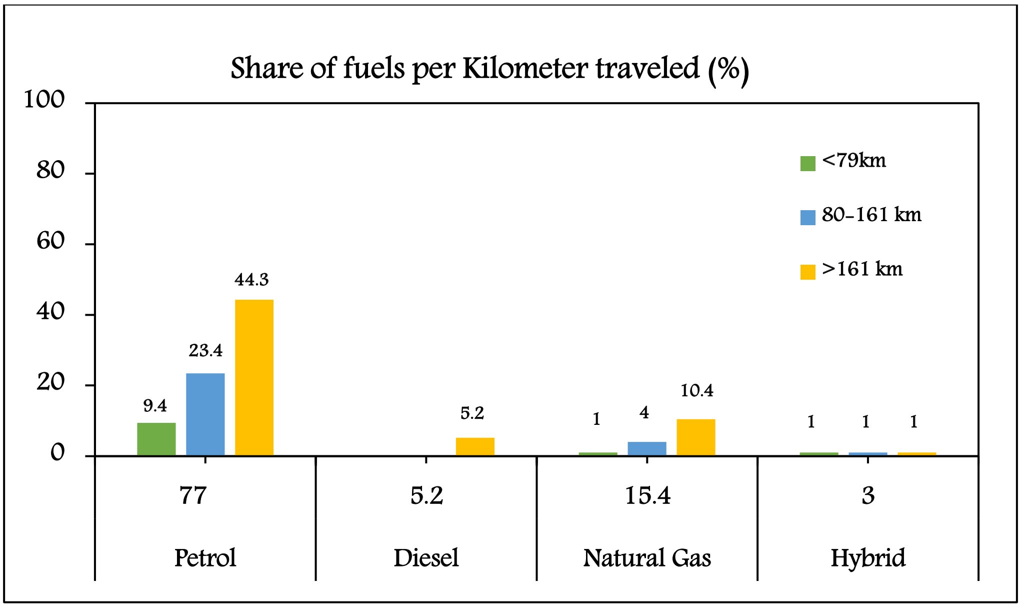

Fig. 1. Vehicle fleet composition as the input of IVE model

$$PRM\ Index = \frac{Velocity}{Speed\ Divider} \tag{4}$$

In this study, a comprehensive analysis of the fleet composition was conducted through a field survey, encompassing diverse fuel types, various systems, production years, emission standards, and vehicle classes (engine volume or weight). Fleet emission rates were computed using the IVE database of the emission rates for each vehicle technology. Additionally, the investigation considered real-world driving behaviors influenced by drivers and distances to administrative service offices. Dynamic variables such as road length, obstacles, traffic timing, and average emission factors for CO, VOC_s, NO_x, SO_x, and PM emissions were calculated for diesel, petrol, natural gas, and hybrid-fueled vehicles (Johnson, 2014; Shahbazi et al., 2016).

RESULTS AND DISCUSSION

Inventory Vehicle Emissions

Fig. 1 visually presents the fleet composition information extracted from the IVE model.

As described in the methodology, Fig. 1 depicts the fleet composition input into the IVE model. In Fig. 1, the fleet composition is as follows: 77% of the fleet comprised petrol vehicles (the most used fuel), 5.2% were diesel, 3% were hybrid, and 15.4% were natural gas vehicles. Among petrol-fueled vehicles, 44.3% covered distances exceeding 161 km, while 23.4% traveled between 80-161 km, and 9.4% traveled less than 79 km. The entire diesel-fueled fleet traveled distances surpassing 161 km. In the natural gas fleet, 1% traveled less than 79 km, 4% traveled between 80-161 km, and 10.4% traveled more than 161 km. Notably, hybrid-fuel vehicles exhibited an equal distribution across the three distance categories (1% each).

As shown in Fig. 2, the estimations pertain to the commute within different fuel categories (such as petrol, natural gas, hybrid, and diesel) and are associated with the service and emission inventory related to the commute. These estimations were obtained from IVE and are segregated according to various fleet categories based on the Euro emission standards.

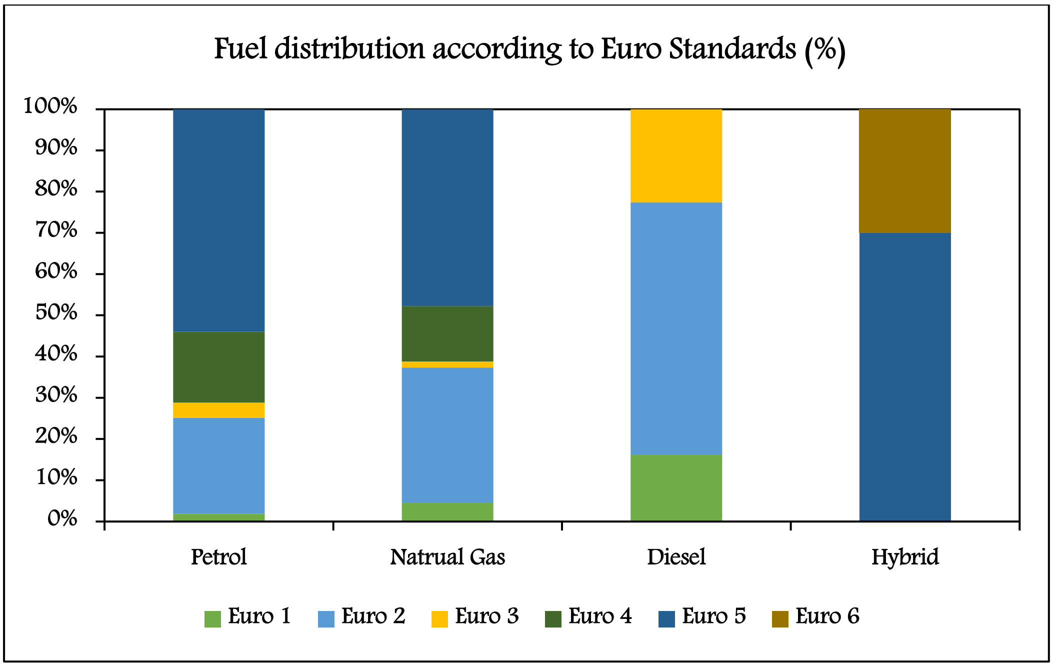

Fig. 2. Emission sharing percentage based on the Euro emission standard for fuel categories related to administrative services.

The figure illustrates the emission inventory estimates for morning heavy traffic, categorized based on different vehicle groups determined by their Euro emission standards. The IVE model is employed for this classification. These estimates are then multiplied by traffic activity data to comprehensively assess pollutant emissions.

The results presented in the figure outline the distribution of vehicles with varying Euro emission standards across distinct fuel types. The findings reveal that approximately half of the petrol-fueled fleet in this study conforms to the Euro 5 standard. Conversely, Euros 1 and 3 standards make up a smaller percentage. Among the natural gas-fueled vehicles, a substantial portion adheres to Euro 5 and 2 standards, while Euro 1 and 3 standards constitute a minor share. Diesel-fueled vehicles are categorized into three classes: Euro 1, 2, and 3, with Euro 2 standards representing the most significant portion. Hybrid-fueled vehicles exclusively fall within the Euro 5 and 6 categories, and the Euro 6 standard dominates the composition of the hybrid fuel fleet. Furthermore, the Euro 6 emission standard has been solely detected in hybrid vehicles, with little to no representation in other types of vehicles. As a result, the calculated emissions amount to 87.5 tons/h for CO, 7 tons/h for NO_x, 12 tons/h for VOC_s, 0.4 tons/h for SO_x, and 1 ton/h for PM.

From a border perspective, the study finds that CO constitutes the primary contributor to emissions by weight, accounting for approximately 81% of total emissions. The remaining emissions are primarily composed of VOC_s and NO_x at approximately 11.11% and 6.52%, respectively, with the remaining portion distributed between PM and SO_x.

As the result shows, natural gas-fueled vehicles are the primary contributors to emissions of VOC_s and NO_x. Additionally, among petrol-fueled vehicles, private cars and taxis are responsible for the highest emissions of CO, VOC_s, and NOx. On the other hand, buses account for the largest share of emissions in diesel fuel vehicles, particularly in terms of SO_x, NO_x, and PM emissions.

A study conducted by Patiño-Aroca et al. concerning vehicle emissions in Ecuador supports these findings. It revealed that CO and VOC_s emissions are predominantly attributed to light

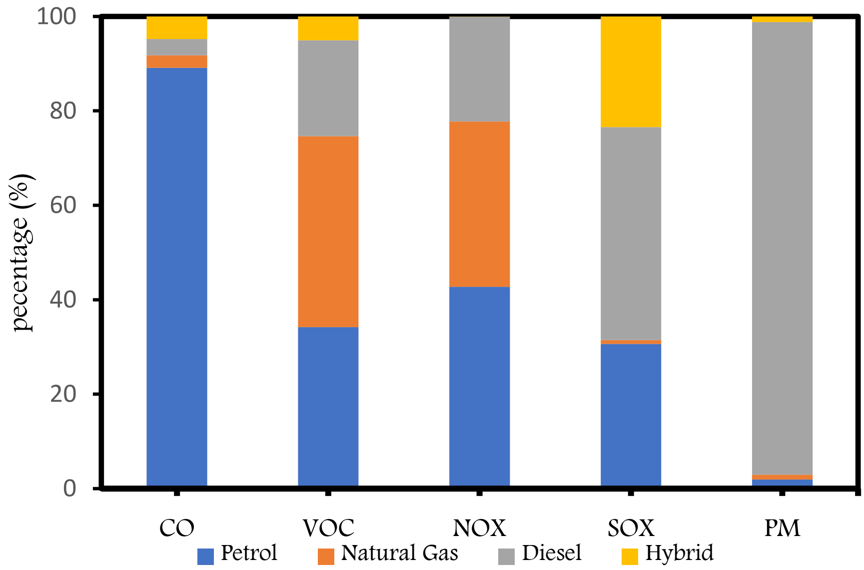

Fig.3. The emission inventory by fuel category for Fleet related to administrative services.

petrol vehicles, while emissions of SO_x, PM, and NO_x primarily originate from buses and heavy diesel trucks (Patiño-Aroca et al., 2022). The results align with the observations of this study.

This figure and the corresponding findings are valuable for understanding the distribution of emissions from different vehicle types and Euro emission standards, which can aid in formulating targeted policies and strategies to reduce pollutant emissions from heavy traffic and improve air quality.

This is represented in Fig. 3, which depicts criteria pollutants from various vehicle fleets in Karaj and summarizes the total values of each pollutant generated by each vehicle category, with CO generation being higher than the other pollutants. It is evident that the most polluting fleets, consisting of petrol and natural gas vehicles, are significant contributors to the emissions of two pollutants: CO (carbon monoxide) and NO_x (nitrogen oxides). Specifically, the figure shows a breakdown of emissions by different vehicle types based on their fuel source. It highlights that petrol-fueled vehicles significantly contribute to CO emissions, whereas natural gas-fueled vehicles are the primary sources of NO_x and VOC_s emissions in Karaj. Furthermore, the provided information references an additional study conducted by Gao et al. in the Harbin-Changchun Megalopolis (HCM), China, and Cuba et al. 2021, which also employed the same IVE model (Cuba et al., 2021; Gao et al., 2020b). According to the findings of these studies, CO emissions from petrol-fueled vehicles emerged as a significant contributor to urban air pollution, paralleling the Karaj study's outcomes.

Moreover, both Karaj and Gao et al. studies identify diesel-fueled vehicles as the primary sources of two pollutants: NO_x and Particulate Matter (PM). These emissions from diesel-fueled fleets constitute a significant portion of the total emissions in both regions, highlighting their substantial impact on air quality. A comparison between the Karaj and HCM studies highlights the similarities in emission patterns, particularly concerning the influence of petrol and diesel-fueled vehicles on CO, NO_x, and PM emissions. Also, this situation is similar to that presented by the Ministry of the Environment of Peru, where it indicates that the main generators of PM_{10} and NO_x are diesel-fueled vehicles (MINAM, 2015).

Furthermore, in the studies by Bari et al., heavy car vehicles are recognized as the primary contributors to sulfur oxides (SO_x). These emissions from diesel-powered fleets emphasize their

Table 1. Description of the Scenario Setting

Scenarios	Scenario targets	Scenarios Description
S0		Considering the current emission situation related to fleet-commutes for administrative services.
S1	Reduction in referrals per service	S11: Reducing commute through one-time referrals per service. S12: Reducing commute by 50% through one-time referrals and 50% through two-time referrals per service. S13: Reducing commute by 50% through one-time referrals and 50% through three-time referrals per service. S14: Reducing commute by 20% through one-time referrals and 80% through two-time referrals per service. S15: Reducing commute by 80% through one-time referrals and 20% through three-time referrals per service.
S2	Replacing the Hybrid fleet	S21: Using 15% of the Hybrid fleet and 5% of the Natural Gas fleet S22: Using 20% of the Hybrid fleet and 10% of the Natural Gas fleet S23: Using 30% of the Hybrid fleet and 20% of the Natural Gas fleet
S3	Replacing the Natural Gas fleet	S31: Using 15% of the Natural Gas fleet and 5% of the Hybrid fleet S32: Using 20% of the Natural Gas fleet and 10% of the Hybrid fleet S33: Using 30% of the Natural Gas fleet and 20% of the Hybrid fleet

significant influence on air quality. A comparison between the Karaj and studies conducted at toll plazas in India indicates similarities in emission patterns, specifically concerning the impact of heavy car vehicles on SO_x emissions. This information can be crucial for policymakers and researchers as they work towards implementing targeted measures to reduce specific pollutants based on the predominant sources identified in each region (Bari et al., 2023).

Setting of vehicle emission reduction scenarios

The study develops three emission reduction scenarios, considering the current situation of vehicle pollutants and strategies for mitigating vehicle emissions. Specifically, this study reports on the emission levels of criteria air pollutants such as CO, VOC_s, NO_x, SO_x, and PM. These emissions are detailed in Table 1, along with descriptions of the three emission control scenarios, which involve reducing in-person administrative centers referrals and replacing the hybrid and natural gas fleets.

Establishing the baseline emission scenario requires assessing various control measures, a pivotal task in devising effective vehicle emission reduction strategies. The baseline scenario (S0) outcomes reveal that commuter vehicle emissions for CO, VOC_s, NO_x, SO_x, and PM amount to 46.3, 3.9, 5.7, 0.09, and 0.06 grams per service, respectively. Further analysis of the emission reduction scenarios holds promise for enhancing the current state of the fleet in Karaj.

Table 1 shows three distinct scenarios: the current situation (S0), the reduction of referrals to administrative offices (S1), and the replacement of the fleet of hybrid and natural gas fuel vehicle fleets (S2 and S3). These scenarios aim to encourage individuals requiring transportation to reach administrative service offices, and This scenario could explore the impact of adopting more environmentally friendly fuel options. This approach is anticipated to lead to a reduced frequency of commutes, ultimately contributing to decreased air pollution emissions. The base scenario evaluates air pollutant emission reduction in the studied fleet by implementing travel demand management practices to reduce referrals. This could include strategies like online

Table 2. The Results of the Scenario Development and their Efficiency

Scenarios	Sub-Scenario	Unit	CO	VOC_s	NO_X	SO_X	PM
S0		g/service	46/31	3/9	5/7	0/09	0/06
S1	S11	g/service	17/006	0/56	2/11	0/04	0/02
		Efficiency (%)	-63/28	-63/05	-62/99	-60/72	-63/28
	S12	g/service	26/076	0/85	3/23	0/05	0/03
		Efficiency (%)	-43/69	-43/71	-43/33	-39/76	-43/70
	S13	g/service	34/01	1/12	4/21	0/07	0/043
		Efficiency (%)	-26/56	-39/4	-26/14	-22/22	-26/57
	S14	g/service	20/41	0/67	2/53	0/04	0/03
		Efficiency (%)	-55/93	-55/66	-55/58	-52/86	-55/94
	S15	g/service	30/61	1/00	3/80	0/064	0/038
		Efficiency (%)	-33/90	-33/50	-33/38	-29/29	-33/91
S2	S21	g/service	51/17	1/38	5/23	0/09	0/05
		Efficiency (%)	10/49	-8/70	-8/29	0/69	-21/10
	S22	g/service	63/45	1/30	5/50	0/08	0/04
		Efficiency (%)	37/00	-13/76	-3/53	-7/28	-30/86
	S23	g /service	52/76	1/08	4/08	0/085	0/04
		Efficiency (%)	13/92	-28/36	-28/42	-5/05	-32/43
S3	S31	g/service	66/31	1/50	5/85	0/09	0/05
		Efficiency (%)	43/19	-0/62	2/59	-2/83	-16/14
	S32	g/service	84/61	1/57	6/66	0/08	0/04
		Efficiency (%)	82/70	4/25	16/86	-11/24	-23/36
	S33	g/service	78/71	1/34	5/72	0/08	0/04
		Efficiency (%)	41/16	-12/30	0/29	-15/88	-37/72

services, appointment scheduling, or centralized administrative service centers to minimize travel for administrative purposes.

Analysis of emission reduction scenarios results

As Table 2 shows, in S11, the reduction in the number of vehicles translates to a diminished demand for administrative service travel, potentially leading to a 75% reduction in commute vehicles. This adjustment holds the promise of curbing PM emissions by 63%. This finding aligns with studies by Okokon et al. and Johansson et al., which highlight PM as a pivotal air pollutant arising from commuting (Johansson et al., 2017; Okokon et al., 2017).

Furthermore, S11 demonstrates an overall affirmative impact on reducing various air pollutants. The effectiveness of curbing CO, VOC_s, NO_x, and SO_x emissions is approximately 60%, highlighting the significant role of commute reduction in mitigating air pollution.

Within S12 and S14, modifying one-time referrals to 50% and distributing a 20% contribution to one-time referrals (per service) and an 80% contribution to two-time referrals (per service) showcases observable reductions in various pollutants (around 40-50%). Among these, PM and CO emissions exhibit the most pronounced reduction efficiency, with SO_x showing relatively less reduction efficiency compared to other pollutants.

Table 2 further details the outcomes of S13 and S15, revealing higher emissions compared to S11, S12, and S14. Particularly noteworthy is the significant impact on VOC_s in S13. Here, a 50% reduction in one-time referrals coupled with another 50% reduction in three-time referrals correlates with increased VOC_s emissions per service, while the remaining variables exhibit similar emission ranges. In S15, total emissions exceed those of S3, yet an 80% decrease in one-time referrals and a 20% decrease in three-time referrals yield lower SO_x emissions compared to other pollutants.

Furthermore, S3 shows the most pronounced impact on emissions increases and exhibits a detrimental influence on various pollutant levels. S32, by comparison, demonstrates a lower efficiency in reducing emissions compared to other scenarios, with reduction rates for CO, VOC_s, NO_x, SO_x, and PM amounting to 82.7%, 4.25%, 16.86%, -11.24%, and -23.36%, respectively.

This scenario aligns with the findings of the study conducted by Xue et al., wherein the replacement of fleet vehicles with varying natural gas and hybrid fuel compositions resulted in a significant increase in CO emissions (Xue et al., 2022). Interestingly, despite efforts to reduce PM emissions from 15% to 37%, this scenario underscores the limitations of hardware-based control and air pollution management strategies.

The considerable variation in reduction effects across scenarios can be attributed to the notable CO emissions from hybrid and natural gas vehicles (S2 and S3). A similar study by Song et al. and Chen et al. also highlighted the elevated presence of CO in hybrid and natural gas vehicles (Chen et al., 2024; Song & Hao, 2019).

According to Table 2, the efficiency of NO_x emissions reduction in S3 has increased when compared to S1 and S2. This observation implies that replacing the fleet with natural gas and hybrid fuels not only fails to mitigate NO_x emissions but also results in a 16% increase. This trend aligns with the findings of Gao et al. and Li et al. concerning PM emissions (Gao et al., 2020a; Geng et al., 2013; Li et al., 2021). On the other hand, S2 demonstrates an effective reduction strategy by replacing fuel sources, resulting in a 21% reduction in PM and a 28% reduction in NOx emissions. This is in line with the conclusions drawn from the research of Patiño-Aroca et al., which identified buses as a significant source of NO_x and PM_{10} emissions (Patiño-Aroca et al., 2022).

Overall, S1 emerges as the most effective scenario for reducing NO_x emissions, with an estimated reduction ranging from 25% to 63%. The results highlight a substantial reduction in VOC_s emissions, decreasing from 3.9 to 0.59 grams per service in S11. The slightest reduction in VOC_s emissions occurred in S31 (0.62), while an increase was observed in S32 (4.25%). It is noteworthy that while S1 exhibits considerable efficacy in emission reduction, S13 shows comparatively less reduction due to 50% of referrals being associated with more than three times per service.

The analysis outcomes for various scenarios regarding SO_x emissions are presented in Table 2. Notably, after S1 (which entails reduction through referral systems), the scenario involving the replacement of the fleet with natural gas fuel (S31) emerges as a pivotal strategy for curtailing vehicle-related SO_x emissions. This scenario underscores that all varieties of replacing the fleet with natural gas fuel yield a decrease in SO_x emissions, effectively mitigating their impact on air quality. However, it is essential to highlight that the efficacy of SO_x emissions reduction in S32 and S33 is relatively diminished compared to other strategies. Specifically, the reduction rates for SO_x emissions in these scenarios are 11.24% and 15.88%, respectively. This indicates their lower effectiveness in mitigating SO_x pollution than the other strategies explored.

This outcome resonates with the findings of Mohammadiha et al., who emphasized the positive impact of fuel quality improvement on SO_x and PM emission reduction (Mohammadiha et al., 2018). Throughout the comparative assessment of different air pollutant reduction scenarios, S11 emerges as the most impactful policy for curbing PM emissions. This scenario, centered around the software sector and transportation demand management (TDM), focusing on reducing commuting with one referral per service, consistently remains effective, leading to a substantial 63% reduction in air pollutant emissions.

The scenario analysis yields valuable insights into strategies for mitigating emissions stemming from commutes. Primarily, reducing people's referrals per service demonstrates its efficacy in decreasing overall commutes and significantly influencing the reduction of PM emissions (Hulkkonen et al., 2020). Hence, decision-makers should prioritize TDM strategies in this domain to lessen commuting and curb PM and other air pollutants.

Secondly, replacing fleets with hybrid fuels and natural gas is explored. The findings underscore that advocating for vehicles utilizing hybrid fuels has a more pronounced impact on emissions reduction compared to natural gas fuels (Anser et al., 2023; Vega-Perkins et al., 2023). These findings further accentuate the positive influence of reducing commutes through referral systems and shared transportation options on air pollutant emissions, particularly for PM, CO, VOC_s, NO_x, and SO_x. Integrating such scenarios into comprehensive strategies can foster improved air quality and the adoption of sustainable transportation practices. By embracing measures to diminish commute demand and associated emissions, cities can take substantial strides toward creating healthier and cleaner urban environments for their residents (Popescu, 2022).

CONCLUSION

In conclusion, utilizing the IVE model has facilitated the creation of one of the initial air pollutant emission inventories for commuting in Karaj city. This research reveals that commutes for administrative purposes in Karaj produced 46.31 g CO, the predominant pollutant. The findings of the base scenario revealed that the emissions of other criteria pollutants in commute with the purpose of administrative services in Karaj are 3.9 g for VOC_s, 5.7 g for NO_X, 0.09 g for SO_x and 0.06 g for PM_{10} per service.

Examining three distinct emission reduction scenarios is promising to address the current situation of vehicle emissions. These scenarios include reducing people's referrals (instead of several times) by referring once per service and replacing vehicles with natural gas fuel and hybrid fuel instead of using diesel and petrol vehicles. After evaluating these scenarios, it becomes evident that S1 represents the most optimal strategy within the fleet. This scenario is poised to yield the most effective reduction in air pollutants. In this scenario, by reducing commutes to one time per service, the overall number of referrals is lowered from 2,000 to 500 times, and the total kilometers traveled drops from 12,265 to 4,600 kilometers per service. This substantial reduction underscores the significant impact of curbing emissions of standard pollutants.

Considering that metropolitan areas often witness vehicle fleets contributing significantly to CO and NO_x emissions, it is reasonable to conclude that S1 emerges as the most suitable scenario for reducing pollutant emissions. Furthermore, both S1 and S2 exhibit a noteworthy reduction in the emission rate of PM associated with commutes. Additionally, the emission rate of NO_x sees a considerable decrease, with S1 standing out as the most influential scenario in terms of emission reduction across various pollutants.

This analysis demonstrates that reducing commutes to offices per service leads to a substantial decline in emissions stemming from mobile sources. Focusing on the software aspect of air pollution reduction management has led to further impacts in conjunction with economic cost reduction.

The findings emphasize the significance of TDM and travel intent reducing commutes. These elements should not be disregarded when aiming to decrease air pollution. Strategic planning and the formulation of strategies to minimize the frequency of commuting play a crucial role in emission reduction and control.

Finally, this study also faced challenges in data collection due to the COVID-19 pandemic, impacting its efficiency. The reliance on standard scenarios introduces uncertainty in projecting future emissions. While recognizing these limitations, the study offers valuable insights, paving the way for future research to refine and enhance the accuracy of assessments.

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CONFLICT OF INTEREST

The authors declare that there is not any conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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