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The Impacts of Sidewalk Autonomous Delivery Robots on Vehicle Travel and Emissions A Focus on On-Demand Food Delivery

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Publication Date

2024-06-18

DOI

10.17610/T64K6F

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The Impacts of Sidewalk Autonomous Delivery Robots on Vehicle Travel and Emissions

A Focus on On-Demand Food Delivery

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Client: Carl Hansen, Coco Delivery

June 2024

Technical Report Documentation Page

1. Report No. N/A	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle The Impacts of Sidewalk Autonomous Delivery Robots on Vehicle Travel and Emissions A Focus on On-Demand Food Delivery		**5. Report Date** June 17, 2024 **6. Performing Organization Code** UCLA-ITS
7. Author(s) Yu-Chen Chu		**8. Performing Organization Report No.** LAS2409
9. Performing Organization Name and Address Institute of Transportation Studies, UCLA 3320 Public Affairs Building Los Angeles, CA 90095-1656		**10. Work Unit No.** N/A **11. Contract or Grant No.** N/A
12. Sponsoring Agency Name and Address UCLA Institute of Transportation Studies www.its.ucla.edu		**13. Type of Report and Period Covered** Final **14. Sponsoring Agency Code** UC ITS
15. Supplementary Notes doi:10.17610/T64K6F		

16. Abstract

In this study, I explore the potential of Sidewalk Autonomous Delivery Robots (SADRs) to alleviate traffic congestion and reduce emissions, with a particular focus on the on-demand food delivery industry. As online food delivery continues to expand, the number of delivery vehicles on urban roads has increased, exacerbating traffic congestion and vehicle emissions. SADRs, characterized by their small size, fully electric operation, and primarily sidewalk-based movement, are emerging as a promising technology to mitigate these issues. However, past research on the traffic and environmental impacts of SADRs within the context of on-demand delivery services remains limited.

To address this research gap, I utilized data from Coco Delivery, a SADR company based in Los Angeles. Combining these data with continuous approximation (CA), the EMFAC2021 data, and the eGRID dataset, I estimated the vehicle miles traveled (VMT) and emissions of conventional human-operated delivery vehicles under three different scenarios. I then compared these results with corresponding data from SADRs to evaluate their effectiveness in reducing VMT and emissions under the same delivery demands.

The findings indicated that SADRs can eliminate 0.7 to 1.59 VMT per order and reduce various types of emissions by 67% to 99.9% under different scenarios. These results suggest that cities should consider SADRs as an effective tool for reducing road traffic and emissions.

17. Key Words new mobility, clean vehicles, Los Angeles, transportation, California, vehicle miles traveled, sustainability	**18. Distribution Statement** No restrictions.

19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 42	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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This report was prepared in partial fulfillment of the requirements for the Master in Urban and Regional Planning degree in the Department of Urban Planning at the University of California, Los Angeles. It was prepared at the direction of the Department and of Carl Hansen from Coco Delivery as a planning client. The views expressed herein are those of the authors and not necessarily those of the Department, the UCLA Luskin School of Public Affairs, UCLA as a whole, or the client.

The Impacts of Sidewalk Autonomous Delivery Robots on Vehicle Travel and Emissions

A Focus on On-Demand Food Delivery

UCLA Institute of Transportation Studies

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Executive Summary

Purpose

In this study, I explored the potential of Sidewalk Autonomous Delivery Robots (SADRs) to alleviate traffic congestion and reduce emissions, with a particular focus on on-demand food delivery industry. As online food delivery continues to expand, the number of delivery vehicles on urban roads has increased, exacerbating traffic congestion and vehicle emissions. SADRs, characterized by their small size, fully electric operation, and primarily sidewalk-based movement, are emerging as a promising technology to mitigate these issues. However, past research on the traffic and environmental impacts of SADRs within the context of on-demand delivery services remains limited.

Method

To address this research gap, I utilized data from Coco Delivery, a SADR company based in Los Angeles. Combining these data with continuous approximation (CA), the EMFAC2021 data, and eGRID dataset, I estimated the vehicle miles traveled (VMT) and emissions of conventional human-operated delivery vehicles under three different scenarios. I then compared these results with corresponding data from to evaluate their effectiveness in reducing VMT and emissions under the same delivery demands.

Findings

The findings indicated that SADRs can eliminate 0.7 to 1.59 VMT per order and reduce various types of emissions by 67% to 99.9% under different scenarios. Given that over 4,300 restaurants in Los Angeles offer delivery services (DoorDash, n.d.), deploying SADRs for just three deliveries per day could lead to an annual VMT reduction ranging from 3,295,950 to 7,786,515. This deployment could also result in a carbon equivalent emission reduction of 351.2 to 659.6 tons for electric vehicles, and 2596.1 to 4547.9 tons for gasoline-fueled vehicles.

Policy Recommendation

Based on the results, I have two recommendations for policymakers:

1. **Promote SADR Adoption:** Governments should consider SADRs as strategic solutions to reduce traffic congestion and emissions by implementing supportive regulations and replacing conventional delivery vehicles, which generate more VMT and emissions per delivery.

2. **Develop SADR-friendly Sidewalk Infrastructure:** Improving sidewalk quality to accommodate SADRs will not only help prevent sidewalk congestion but also enhance accessibility for disabled travelers. These individuals benefit from the same infrastructure improvements as SADRs, such as wider and barrier-free pathways.

Keywords: Sidewalk Autonomous Delivery Robots (SADRs), On-Demand Food Delivery, Vehicle Miles Traveled (VMT), Emissions

1. Motivation

The online food delivery industry has experienced remarkable growth in recent years, with its revenue tripling over the past five years (Statista, n.d.). This surge, characterized by small but frequent deliveries, has resulted in an increase in delivery vehicles on urban roads. This exacerbates traffic congestion and greenhouse gas (GHG) emissions, which in California conflicts directly with the state's climate goals.

Notably, most online food orders are of small size and occur within a two-mile radius, creating an ideal environment for the adoption of Sidewalk Autonomous Delivery Robots (SADRs). These robots are fully electric, compact, and operate exclusively on sidewalks and in crosswalks, offering the potential to mitigate road congestion and emissions. However, research on SADRs remains limited, with existing studies primarily focusing on parcel delivery and often comparing SADRs to conventional delivery vans. This leaves a notable gap in understanding the environmental and traffic impacts of SADRs, particularly in comparison to human-operated deliver vehicles for on-demand delivery services.

To quantify the impacts of SADRs, I addressed two critical research questions:

1. How do SADRs compare to conventional human-operated deliver vehicles in terms of vehicle miles travel (VMT) and emissions, specifically in the context of food delivery?
2. Can SADRs serve as an effective solution for reducing traffic congestion?

I structure the study as follows: I began with a comprehensive literature review on on-demand food delivery and SADRs, followed by an estimation and comparison of VMT and emissions for SADRs and conventional human-operated delivery vehicles. This comparison was based on a combination of datasets from Coco Delivery, eGRID, and EMFAC. In the end, I concluded with policy recommendations and a discussion of its limitations.

2. Literature Review

2.1. On-Demand Food Delivery

2.1.1. The Growing Market of On-Demand Food Delivery

The on-demand food delivery (ODFD) industry has witnessed significant growth in recent years, fundamentally altering how we access food, enhancing convenience, and influencing lifestyle changes (Allen et al., 2021; Li, Mirosa, & Bremer, 2020; Liu, Hao, Liao, Boriboonsomsin, & Barth, 2023). It is projected that the global revenue for online food delivery, which stood at US$923.1 billion in 2023, will surge to US$1,465.6 billion by 2027 (Statista, n.d.). The United States boasts the second-largest online food delivery market, second only to China. This market is primarily divided into two segments: meal delivery and grocery delivery. Meal delivery involves the online ordering and delivery of prepared meals for immediate consumption, while grocery delivery pertains to the online ordering and delivery of unprepared food items, beverages, and household or personal care products.

The online food delivery market in the U.S. is substantial. By 2023, the grocery segment market was valued at approximately US$183 billion, whereas the meal delivery sector's revenue was about US$87 billion (Beyrouthy, 2023). Additionally, the meal delivery segment is expected to have about 25.2% of potential customers using the service in 2023, with the potential to expand the user base to an estimated 2.5 billion customers by 2028 (Statista, n.d.).

2.1.2. The Models, System, and Delivery Characteristics of On-Demand Food Delivery

Two primary models define the ODFD industry: Restaurant-to-Consumer and Platform-to-Consumer delivery systems. In the former, restaurants like KFC, McDonalds, and Dominos are responsible for both food preparation and delivery, whereas Platform-to-Consumer systems involve third-party platforms like UberEats, DoorDash, and GrubHub that partner with various restaurants to offer delivery services (Lyons, n.d.).

There has been a global upsurge in the number of food delivery platforms, which serve as marketplaces where consumers can order meals from a variety of local restaurants. These platforms derive income by taking a commission from each sale and charging customers for delivery (Alvarez-Palau et al., 2022).

The operational procedure for these food delivery platforms is as follows (Alvarez-Palau et al., 2022; Liu et al., 2023):

1. Customers place orders through the platforms.

2. The platforms validate the order with the restaurant, which provides a preparation completion time. Concurrently, the platform estimates a delivery time and notifies nearby riders—who are evaluated based on proximity and platform rating—to pick up the order.
3. The first rider to respond is assigned the task.
4. The rider then picks up the meal from the restaurant and must deliver it within a predetermined time limit.
5. Once the delivery is complete, the rider becomes available for new orders.

Those delivery drivers, commonly referred to as "riders," are a local network of independent drivers who engage with delivery platforms on an independent contract basis, earning income per delivery (Li, 2020; Alvarez-Palau et al., 2022). These individuals use their personal vehicles to transport food from restaurants to customers' locations. This system is known as "crowdsourced delivery," an evolving aspect of the "sharing economy." (Alnaggar et al., 2021) This approach helps reduce costs and accelerate deliveries to meet the instantaneous demands of food delivery services. (Dai & Liu, 2020; Alnaggar et al., 2021; Savelsbergh & Ulmer, 2022).

To ensure food quality and satisfy customer expectations, urban food deliveries are usually restricted to short distances, often under 3 miles (Allen et al., 2021). This proximity allows for rapid delivery times, usually ranging between 15 and 45 minutes from the moment an order is placed to the time it reaches the customer (Cant, 2019). The brevity of these trips makes diverse transport options viable, including motorcycles, bicycles, cars, and vans (Allen et al., 2021).

While detailed data on the specific vehicular makeup and the frequency of deliveries are scarce, a case study on the London food delivery market provided some insights. Allen et al. (2021) found that mopeds made up 83% of delivery vehicles, followed by cars (10%) and bicycles (7%). The study also indicated that a delivery vehicle averages 9.6 deliveries per day, with each trip lasting about 25 minutes and spanning 1.4 miles, totaling approximately 25.7 miles traveled daily per vehicle.

2.1.3. The Negative Impacts of On-Demand Food Delivery

While ODFD has been lauded for its economic benefits and convenience (Lin et al., 2018; Guo et al, 2019), its rapid growth also comes with a set of environmental and transportation challenges, including traffic congestion (Iwan et al., 2016; Guo et al., 2019), air pollution (Weiss & Onnen-Weber, 2019), increased carbon emissions (Zhang et al., 2019; Schnieder et al, 2021b), reduced urban space (Rai et al., 2018; Schnieder et al, 2021a), and causing negative health impacts to delivery drivers (Li et al., 2020; Boysen et al, 2021; Schnieder et al, 2022).

Unlike conventional long-haul freight services, ODFD operates under a different logistical paradigm. ODFD orders tend to be small, frequent (Morganti & Gonzalez-Feliu, 2015; Iwan et al., 2016), geographically scattered across cities, and often entail complex logistics (Morganti & Gonzalez-Feliu, 2015). Additionally, ODFD typically originates from local businesses, not centralized warehouses, and employs a range of transport options — from mini-vans and personal cars to bicycles and walking. (Lee et al., 2016; Shaheen et al, 2020; Ai, Zheng, Chen, & Kawamura, 202). This diversity in scale and mode challenges operational efficiency, particularly in the last-mile delivery segment (Macharis & Melo, 2011; Rodrigue, 2020).

Allen et al. (2021) provided a stark quantification of these issues, comparing GHG emissions and space occupancy among different types of vehicles used in ODFD and conventional delivery in London in 2017. The study revealed that the vehicle miles traveled (VMT) and GHG emissions for ODFD were significantly higher compared to conventional delivery methods or even cooking at home. Specifically, VMT for ODFD were 40 to 1,300 times higher than conventional delivery. The GHG emissions also varied by the type of vehicle used—cars generated 716 kg CO_2e/t (carbon dioxide equivalent per ton delivered), mopeds 340 kg CO_2e, and bikes only 64 kg CO_2e, in stark contrast to conventional delivery vehicles, such as vans and heavy goods vehicle (HGV), that only generated 3 to 33 kg CO_2e/t. Additionally, cars and mopeds used for ODFD occupied significantly more curb space, with 1620 m^2hrs/t (square meter curb occupied by vehicle while parked per hour per ton delivered) and 323 m^2hrs/t respectively, compared to 2 to 127 m^2hrs/t for conventional delivery vans. The study also highlighted that the VMT and GHG emissions of ODFD were 20 times and 2 to 4 times higher, respectively, than the cook-at-home option on a weekly grocery shopping basis.

Other studies have reported similar findings. Lin et al. (2018) observed that although crowdsourcing can expedite and reduce the cost of delivery services for customers, it may result in higher fuel consumption and emissions owing to the supplementary vehicle detours prompted by real-time demand. Similarly, Schnieder et al. (2022) employed microscopic traffic simulations to evaluate the emissions from on-demand meal delivery services and concluded that, in comparison to scenarios without delivery services, CO_2 emissions can rise by as much as 21% per kilometer if personal motor vehicles were used.

In conclusion, the environmental and transportation challenges stemming from the growing demand for ODFD necessitate more sustainable and efficient solutions to counteract the adverse effects of increased vehicle usage.

2.2. Sidewalk Autonomous Delivery Robots (SADRs)

2.2.1. SADRs Introduction

Various innovative solutions have been proposed to address the traffic and environmental challenges outlined above, including autonomous driving, drones, cargo bikes, and delivery robots (Boysen et al., 2021). Among these solutions, sidewalk autonomous delivery robots (SADRs) have gained attention due to their potential to reduce delivery costs, enhance delivery efficiency, and mitigate safety concerns for delivery personnel (Jennings & Figliozzi, 2019; Figliozzi & Jennings, 2020).

SADRs, also called Personal Delivery Devices (PDDs), are diminutive, pedestrian-scale robots about the size of a microwave oven that transport goods directly to consumers without the need for human delivery personnel, as shown in **Figure 1**. These electrically powered automatons are designed to navigate exclusively on sidewalks, in crosswalks, and in bike lanes. They are equipped with sensors and advanced navigation technology enabling them to traverse both roads and sidewalks autonomously, without the need for a driver or on-the-spot delivery staff (Jennings & Figliozzi, 2019; Figliozzi, 2020; Clamann et al.,2023). Their sizes, carrying capacities, and operating speeds differ across various companies: typically, they weigh between 40 to 80 pounds, can transport items weighing 21 to 100 pounds, and travel at speeds ranging from 4 to 12 mph (Jennings & Figliozzi, 2019). Although their modest capacity and velocity currently limit their use primarily to restaurant meal deliveries (Jennings & Figliozzi, 2019), there is an emerging trend where they are increasingly utilized for delivering groceries, medical supplies, and other necessities (McClure, 2020).

Figure 1. Photos of SADRs.

Left photo: SADRs from Coco Delivery (Source: Coco Delivery website). Right photo: SADRs from Starship. (Source: Starship website)

2.2.2. SADRs Market

The US market, along with the global scene, features a diverse array of SADR companies. Starship Technologies, established in 2014, asserts that it has completed over 5 million deliveries across numerous cities and academic campuses worldwide (Starship Technologies, n.d.). Meanwhile, Dispatch and Marble, both San Francisco-based startups, were acquired by industry giants—Amazon in 2017 and Caterpillar in 2020, respectively (cbinsights, n.d.; Francis, 2020; PitchBook, n.d.). Serve Robotics, yet another San Francisco-based venture and an UberEats partner, predominantly operates in Los Angeles and San Francisco (Serve Robotics, n.d.). Coco Delivery, launched in 2020, operates within Santa Monica, West Hollywood, and multiple neighborhoods across the City of Los Angeles (Coco Delivery, n.d.; Tracxn, n.d.). Numerous other players in the SADR industry include Kiwibot, Robby Technologies, Thyssenkrupp, Nuro, and

Domino's DRU, among others, with a significant number of these companies having operations or headquarters in California (Jennings & Figliozzi, 2019; Francis, 2019; McClure, 2020). The entire autonomous delivery robot market is estimated to be $2 billion in 2022 and is expected to surpass around $10 billion by the end of 2035 (Research Nester, 2023).

2.2.3. SADRs Regulation

As the market expands and the robots themselves continue to evolve and innovate, state legislatures nationwide are actively developing regulations in an attempt to keep pace with the swiftly advancing technology. Typically, these state laws aim to govern the physical and operational parameters, designated operational zones, requirements for human oversight, and rules concerning the right of way. As of May 2023, 24 states have enacted legislation for PDDs: Arizona, Arkansas, Colorado, Florida, Georgia, Idaho, Indiana, Iowa, Louisiana, Maryland, Michigan, Mississippi, New Hampshire, North Carolina, Ohio, Oklahoma, Pennsylvania, Tennessee, Texas, Utah, Virginia, Washington, West Virginia, and Wisconsin. Conversely, four states have failed to pass such legislation: Kansas, Massachusetts, Missouri, and Oregon. And five states are currently considering legislation: Illinois, Minnesota, Nevada, Rhode Island, and Wyoming. The remaining states have no state legislation (Clamann et al.,2023; Colo. Rev. Stat. § 43-4-1202, 2022; Mississippi S.B. 2508, 2022; New Hampshire H.B. 116, 2022; West Virginia House Bill 4675, 2022).

Most state laws confine PDD operations to sidewalks, crosswalks, or pedestrian areas, though some, such as Indiana, North Carolina, Texas, and Utah, permit PDDs on roadways or highway shoulders. Weight limits for PDDs vary significantly, from 80 to 1,000 pounds. Speed restrictions also vary, with a maximum sidewalk speed limit ranging from 3.5 to 12 mph, and road speed limits from 10 mph to 25 mph. Generally, states mandate that PDDs must yield to pedestrians, avoid obstructing public rights-of-way, and not interfere with other traffic. Arizona uniquely stipulates that PDD operation is only permissible if controlled or monitored by a business entity or an affiliate, ensuring some level of corporate responsibility for these devices.

Given the absence of state-level regulation in many places, some municipalities – such as San Francisco and Los Angeles, California, Chicago, Illinois, and Washington, D.C. – have instituted their own sets of rules for PDDs (Jennings & Figliozzi, 2019; Office of the Mayor, 2022; TX Transp § 552A, 2023). For example, the City of Los Angeles mandates that PDDs must be zero-emission, weigh no more than 100 pounds, and adhere to speed limits—no more than 5 mph on sidewalks and crosswalks, and up to 15 mph on roadway shoulders and roads. PDDs are also not allowed to be parked on sidewalks or in crosswalks. Moreover, Los Angeles requires that each PDD have clear identification, a valid permit, and that operators pay administrative fees. Operating companies are obliged to carry a specified level of insurance coverage. Regarding fleet size, Los Angeles stipulates that operators can manage a maximum of 75 devices within a single

Neighborhood Council[1] Boundary and allows each operator to expand to three Neighborhood Councils, maintaining up to 75 devices in each (Los Angeles Department of Transportation, 2021).

2.2.4. Current Research Related to SADRs

The recent surge in market penetration and advancements in technology has spurred an increase in research on SADRs. Past studies have predominantly examined aspects such as sidewalk safety (Bennett et al., 2021; Gehrke et al., 2023), user perspectives (Martinez et al., 2023; Koh & Yuen, 2023), and the broader mechanical, electrical, or computational design of robots (Du et al., 2018; Wen et al., 2022; PARRAVICINI, 2023; Thiel et al, 2023). Research specifically addressing SADRs within a delivery context is scarce (Jennings & Figliozzi, 2019), although there are inquiries into their environmental, transportation, and economic impacts.

In their study, Figliozzi and Jennings (2020) concluded that SADRs reduce energy consumption and emissions but were less effective than Road Autonomous Delivery Robots (RADRs) for service areas distant from the depot. They noted that while SADRs may decrease VMT on roads, they could exacerbate issues such as sidewalk safety and congestion. Another analysis of autonomous delivery vehicle competitiveness in urban areas determined that the slower speed of SADRs limits their competitiveness, except in scenarios where a mothership[2] was unnecessary, such as proximity to a depot (Figliozzi & Jennings, 2020). Figliozzi (2020) also found that SADRs had lower emissions in last-mile deliveries compared to vans, particularly when a mothership was not utilized. Furthermore, Jennings and Figliozzi (2019) identified specific scenarios where SADRs could significantly reduce on-road VMT, cost, and delivery duration.

Despite the growing body of research on the environmental and transportation effects of SADRs, most studies concentrated on conventional delivery systems, frequently comparing SADRs with conventional delivery vans. There remains a substantial gap in understanding the impacts of SADRs on the environmental and traffic systems associated with on-demand delivery, particularly when compared with conventional delivery vehicles like passenger cars or motorcycles.

To address this research gap, here, I quantified the VMT and emissions of SADRs and compared them with those of conventional human-operated delivery systems. This comparison is critical to evaluate the potential impacts of this emerging technology on traffic and environmental conditions, particularly in the context of last-mile delivery.

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[1] Neighborhood Councils represent the level of government closest to the citizens. They function as advisory bodies that advocate for community interests at City Hall, addressing key issues such as development, homelessness, and emergency preparedness (LACITY.GOV, n.d.).

[2] A mothership is defined as a van equipped to transport SADRs, with a human driver responsible for deploying or retrieving these devices (Figliozzi & Jennings, 2020).

3. Research Methods

I utilized continuous approximation (CA), a specialized logistics method, to model VMT (Jennings, & Figliozzi, 2019; Figliozzi & Jennings, 2020; Ai et al., 2021), drawing on methodologies from Ai et al. (2021). I also used the Emission Factors Model (EMFAC) 2021 developed by the California Air Resources Board (Liu et al., 2023) to model the emissions based on the modeled VMT. The data required for modeling VMT were primarily sourced from Coco Delivery, a Los Angeles-based SADR enterprise. Additionally, emission data for electricity generation was obtained from the eGRID 2022 Data and eGRID 2020 $PM_{2.5}$ Data from United States Environmental Protection Agency (EPA). Energy consumption and emission data for both conventional human-based delivery vehicles and SADRs was estimated based on the VMT figures obtained from the CA model and from Coco Delivery.

3.1. Data Source

3.1.1. SADR Data

For this study, Coco Delivery provided data on merchants, average travel distance, and other related data for 1 March 2023 through 31 May 2023 in their service area, which included the City of Santa Monica and the Westwood district of the City of Los Angeles, both of which are located in Los Angeles County, California, United States. The selected period was chosen because it excluded specific holidays – such as Thanksgiving, Christmas season, and summer break – that can distort estimates of typical travel behavior. All the data were aggregated by day. The list of variables included in the original dataset that were used in this analysis are listed in **Table 1**.

3.1.2. EMFAC2021 Data

The EMFAC2021 is the latest emissions inventory model that calculates emissions from motor vehicles operating on California roads. It can be used to analyze how motor vehicle emissions in California have changed over time and how they are projected to change in the future. The EMFAC2021 incorporates the most recent data on California's car and truck population, activity, and emission testing. It covers ten common emissions, including carbon dioxide (CO_2), nitrogen oxides (NO_x), hydrocarbons (HC), particulate matter (PM), and others, as well as fuel and energy consumption (California Air Resources Board, 2021). The modeling results were used to estimate the emissions from conventional, human-operated delivery vehicles.

Table 1. List of Variables Provided by Coco Delivery

VARIABLE	DESCRIPTION
Average Delivery Distance (mi)	The mean distance a SADR delivery covers from a merchant to a customer within a single day.
Total Delivery Distance (mi)	The cumulative distance covered by all SADR deliveries from a merchant to customers in a day.
Average One Way Trip Time (min)	The mean time taken for a SADR delivery to reach a customer from a merchant on any given day.
Average Round Trip Time (min)	The average time a SADR takes for a delivery to go from a merchant to a customer and then return to the original merchant or proceed to a different merchant within the same day.
Total CO_2 Emissions Reduced	The amount of CO_2 emissions saved by using SADRs for deliveries, compared to the emissions that would have resulted from the same distance being covered by cars (assuming 400g CO_2 per mile), over the course of a day.
Average Stop Time (mins)	The mean duration a delivery stops at a customer's location.
Total Robot Deliveries	The total number of deliveries executed by SADRs on that day.
Merchants	The number of merchants utilizing SADRs for their food deliveries on that day.
Average Deliveries/Merchant	The average number of deliveries conducted per merchant on a single day.
Average Speed (mph)	The average speed at which a SADR operates while making deliveries.
Unique Bots Deployed	The number of distinct SADRs that are operational in a day
Delivery Distance/Bot (mi)	The average distance covered by each SADR during deliveries in a day.
Energy Consumption	Energy consumed by SADRs per mile traveled

3.1.3. eGRID 2022 Data and eGRID 2020 PM2.5 Data

While electric vehicles do not generate emissions during operation, they are still associated with emissions from electricity generation. The associated emissions used in the study were sourced from the Emissions & Generation Resource Integrated Database (eGRID), which provides comprehensive data on the environmental characteristics of nearly all electric power generated in the United States. eGRID compiles plant-specific data for all U.S. electricity-generating plants that supply power to the electric grid and report data to the U.S. government. The reported data in the eGRID 2022 dataset include net electric generation and seven common emissions, such as CO_2, nitrogen NO_x, and SO_2 (EPA, 2024). The eGRID 2020 dataset includes the emission rate of PM2.5. It is important to note that the years of the two most recent datasets are different: the common emissions data are from 2022, while the PM2.5 data are from 2020. The emission rate of electricity generation per mile was used to estimate the emissions from electric vehicles and SADRs.

3.2. Statistical Methods

3.2.1. VMT Modeling

I used CA to model the VMT associated with on-demand food delivery conducted by conventional human-operated vehicles. I focused on three scenarios (see **Figure. 2**) in the study area, considering factors such as the number of stops, restaurant densities, speed, etc., to estimate the VMT specifically for batched delivery behaviors in conventional human-based delivery systems. The scenarios, detailed by Ai et al. (2021), were developed by three strategies: (1) whether drivers were crowdsourced for delivery tasks; (2) whether food orders were consolidated from multiple restaurants; and (3) whether orders were delivered to multiple customers. Each scenario is outlined below:

1. Scenario 1: One-to-One Delivery. This baseline scenario represents the traditional model of on-demand food delivery, where the driver handles one order at a time. After delivering the order, the driver returns to the original restaurant to pick up the next order. The trip chain, serving a single origin and destination, comprises two segments: delivery and return.

2. Scenario 2: One-to-Many Delivery. In this scenario, a driver serves multiple customers in one trip, picking up various orders from the same restaurant. After delivering all orders in one trip chain, the driver returns to the same restaurant to pick up the next batch of orders. This trip chain includes three types of segments: delivery, customer detours, and return segments, potentially reducing VMT per order due to shared delivery and return segments.

3. Scenario 3: Many-to-Many Delivery. A driver collects meals from multiple nearby restaurants and delivers them to various customers. After completing all deliveries, the driver returns to the original restaurant cluster to pick up the next set of orders. This trip chain involves four types of segments: restaurant detour, delivery, customer detour, and return. Compared to Scenario 2, this scenario has additional detour trips between restaurants.

To model VMT of the five scenarios consistently with previous research, I applied equations from Ai et al. (2021):

$$(1)\ \ Oi = L_i / N_O$$
$$(2)\ \ L_i = \sum_{s} Ls, i\ Qs, i$$
$$(3)\ \ R_i = (O_i - O_1) / O_1$$

Subject to

$$N_O \geq 1$$

where s = trip segment s (as shown in **Table 2**); i = Scenario i; N_O = number of orders; L_i = total VMT for the trip chain under Scenario i; $L_{s,i}$ = length for of trip segment s under Scenario i; $Q_{s,i}$ = number of trip segment s under Scenario i; T_i = total time for each delivery trip chain under Scenario i; and O_i = VMT per order under Scenario i.

Several variables determined the trip segments : n_s = number of stops, n_R = number of restaurants, R_{SA} = restaurant service area, δ_R = restaurant density; k_1 and k_2 = constants. The common values for k_1 and k_2 under the Manhattan metric are 0.97 and 0.82, respectively (Langevin et al. 1996; Lin et al. 2016; Franceschetti et al. 2017; Ai et al.,2021). Here, n_s and n_R indicate the number of stops and restaurants involved in each delivery trip, while δ_R refers to the restaurant density across the entire study area. R_{SA} denotes the service area for each restaurant. In this study, I adjusted R_{SA} to ensure the delivery trip distance was congruent with the SADR ranges, resulting in a much smaller service area compared to where human delivery is available. The values of these parameters for this study can be found in **Table 3**.

I made a number of assumptions to simplify the modeling process. First, for the purposes of comparison, I assumed that all trips made by SADRs would be replaced by delivery drivers, who did not serve areas beyond the range of SADRs. This assumption resulted in relatively small restaurant service areas, as mentioned previously. Second, I assumed each customer place only one order from one restaurant, which is certainly plausible. In Scenario 3, when multiple restaurants were available, each customer ordered from a different restaurant. This setup resulted in delivery trips serving two customers from two restaurants, three customers from three restaurants, and so on.

Table 2. Travel Distance for Trip Segments

TRIP SEGMENT	DISTANCE
Delivery Trip (dl)	$L_{dl} = \frac{k_1}{2}\sqrt{n_s R_{SA}} - \frac{k_2}{2}\sqrt{\frac{R_{SA}}{n_s}}(n_s - 1)$
Detour Customer Trip (dc)	$L_{dc} = k_2\sqrt{\frac{R_{SA}}{n_s}}(n_s - 1)$
Return Trip (rt)	$L_{rt} = \frac{k_1}{2}\sqrt{n_s R_{SA}} - \frac{k_2}{2}\sqrt{\frac{R_{SA}}{n_s}}(n_s - 1)$
Detour Restaurant Trip (dr)	$L_{dr} = k_2\sqrt{\frac{1}{\delta_R}}(n_R - 1)$

Note: n_s = number of stops; n_R = number of restaurants; R_{SA} = restaurant service area; δ_R = restaurant density; k_1 and k_2 = constants.

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Table 3. Descriptive Statistics of CA Parameters

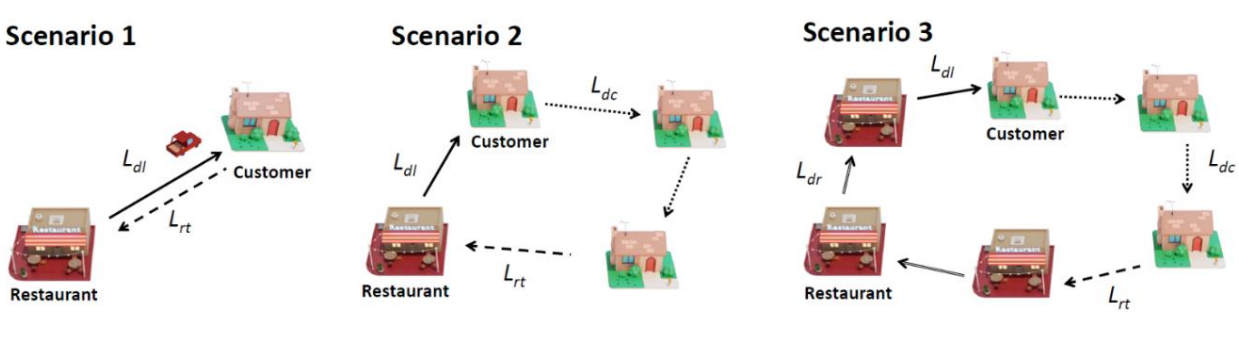
VARIABELS	DESCRIPTION	VALUES
R_{SA}	Restaurant Service Area	2.69 (mi^2)
N_R[1]	Number of Restaurants in the Study Area	56
δ_R[2]	Restaurant Density	1.99 (restaurants/mi^2)

Data Source: Coco Delivery

1. This represents the number of restaurants providing SADR delivery service in the study area.

2. Restaurant density was calculated by dividing the number of restaurants by the study area, which measures 28.07 mi^2.

Figure 2. Trip Segments of Three Delivery Scenarios



3.2.2 Emission Modeling

1. Tailpipe Emissions

I used the EMFAC2021 v1.0.2 web tool to model the tailpipe emissions from fuel-based vehicles and the energy consumption of electric vehicles based on the modeled VMT. The input factors include:

- **Region:** Los Angeles Sub-Area (SC)
- **Calendar Year:** 2023
- **Season:** Annual
- **Vehicle Category:** LDA (passenger cars), MCY (motorcycles)
- **Model Year:** Aggregate
- **Speed:** 10 mph
- **Fuel Type**: Gasoline, Diesel, Electricity, Natural Gas, and Plug-in Hybrid

When selecting the values for the input factors, I chose those that best represent the food delivery environment in the study area. For Region, I selected the Los Angeles Sub-Area (SC), which includes the southern and western parts of the city of Los Angeles. For Calendar Year and Season, I chose 2023 and Annual to align with the dataset obtained from Coco Delivery. For Vehicle Category, I selected LDA (passenger cars) and MCY (motorcycles) as they are the most common vehicles used for food delivery. For Model Year, I used an aggregate to reflect the varied ages of vehicles that potentially provide delivery service. The speed was set at 10 mph, which closely matches the average vehicle speed (10.5 to 12 mph) during noon and dinner times in the study area on a typical weekday, as estimated by Google Maps. All potential fuel types—Gasoline, Diesel, Electricity, Natural Gas, and Plug-in Hybrid—were included to ensure the comprehensiveness of the emission results.

2. Electric Vehicle Emissions

I used the eGRID 2022 Data and eGRID 2020 $PM_{2.5}$ Data to estimate electric vehicle emissions based on the energy consumption from EMFAC2021 modeling results and the SADR energy consumption rate provided by Coco Delivery. State-level data in both eGRID datasets, specifically from California, were selected as the emission rate for electricity generation. The electricity emission rate for California is shown in **Table 4**. Note that I did not consider a grid loss of 5.1% in this study to be consistent with emissions estimates for the delivery robots. While EMFAC2021 includes data on ten types of emissions, eGRID contains only seven types of emissions, including [1]CO_2e[3], carbon dioxide equivalent. To make the emission results comparable, I only estimated the seven emissions calculated by both EMFAC2021 and eGRID:

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[3] CO_2e is a measurement of the total greenhouse gases emitted, expressed in terms of the equivalent amount of carbon dioxide. It is calculated based on the global warming potential of CO_2, CH_4, and N_2O. In contrast, CO_2 measurements account only for carbon dioxide emissions and do not include other greenhouse gases (Harris, 2023; EPA, 2024).

NO_x, CO_2, CO_2e, CH_4, N_2O, SO_x, and $PM_{2.5}$. It should be noted that while eGRID provides SO_2 data, EMFAC2021 provides SO_x data. For simplicity, I treated SO_2 and SO_x as equivalent under the term SO_x. EMFAC2021 does not include CO_2e emissions, however, CO_2e can be calculated based on the global warming potential[4] (GWP) of CO_2, CH_4, and N_2O, all provided by EMFAC2021. I made the calculation method equivalent to that used in eGRID 2022 for consistency, employing the 100-year GWPs and summing the products of each GHG emission value and their GWP. According to eGRID 2022, the GWP of CO_2 is 1, CH_4 is 25, and N_2O is 298. The calculation method is detailed below.

$$CO_2e\ Emissions = (GWPCO_2 \times EmissionsCO_2) + (GWPCH_4 \times EmissionsCH_4) + (GWPN_2O \times EmissionsN_2O)$$

Subject to

$$GWPCO_2 = 1$$
$$GWPCH_4 = 25$$
$$GWPN_2O = 298$$

Table 4. Output Emission Rates of Electricity Generation in California

UNIT	CO_2	CH_4	N_2O	CO_2e	ANNUAL NO_x	OZONE SEASON NO_x	SO_2	$PM_{2.5}$*
lb/MWh	455.94	0.026	0.003	457.49	0.403	0.357	0.015	0.021

Data Source: EPA eGRID 2022 Data and eGRID 2020 $PM_{2.5}$ Data.
**$PM_{2.5}$ data is from 2020, unlike other emissions data which is based on 2022.*

3.3. Limitations

The research method has several limitations. First, the VMT for conventional human-operated vehicles was based on models, not actual data, and did not account for varying urban environments, potentially skewing real-world accuracy. Future studies should track actual delivery paths to obtain more accurate VMT data. Second, the scenarios were oversimplified and did not reflect complex real-world operations like crowdsourced deliveries or situations where multiple orders are delivered to the same customer locations, affecting the comprehensiveness of VMT estimates. Third, the emissions calculations only considered direct emissions and electricity

[4] Global warming potential (GWP) is a value assigned to a greenhouse gas (GHG) that allows the emissions of different gases to be assessed on a basis equivalent to the emissions of the reference gas, CO_2 (EPA, 2024).

generation emissions, omitting well-to-tank emissions which involve the production and distribution of fuel. This oversight means the study likely underestimated the total emissions from delivery vehicles. Lastly, EMFAC2021 used in the study, which provides aggregated vehicle data for California, may not accurately represent the actual delivery vehicles. Furthermore, the aggregated output data was based on speeds, not travel distance, which may not accurately reflect the higher emissions from short, stop-frequent trips typical in delivery scenarios. Future research should consider general conditions of vehicles, such as vehicle model year and brands, and use more precise tools like the EPA's MOtor Vehicle Emission Simulator (MOVES) for better accuracy in stop-frequent trips emission modeling.

4. Research Findings and Discussion

4.1. VMT Modeling Results

In Scenario 1, the baseline model of delivery from one restaurant to one customer, I equated the VMT per order to the VMT of SADRs at 1.59 miles. As illustrated in **Figure 3** and **Figure 4** as the number of orders per trip increased, the VMT per order decreased in both Scenario 2 (one restaurant to multiple customers) and Scenario 3 (multiple restaurants to multiple customers). However, the reduction rate in Scenario 2 was more pronounced (29.3% to 55.3% for 2 to 5 orders) compared to Scenario 3 (14.1% to 25.7% for the same number of orders). This difference was attributed to the absence of restaurant detour trips in Scenario 2. Although Scenario 3 included more detour trips, these were shorter than delivery and return trips, resulting in a lower VMT per order than Scenario 1. Consequently, this suggests that batch deliveries can significantly reduce VMT (though perhaps at the cost of more lukewarm food deliveries).

In contrast to delivery drivers who can perform batched deliveries (Scenarios 2 and 3) depending on the type of vehicle used, SADRs are typically restricted to one-to-one deliveries (Scenario 1) due to their lower cargo capacities. This results in higher VMT for SADRs compared to conventional human-delivery vehicles that implements batched delivery. However, it should be noted that SADRs operate on sidewalks and crossroads, which reduces the number of delivery vehicles on the road. Based on the modeling results, SADRs can decrease road VMT by 0.71 (5 orders in Scenario 2) to 1.59 miles (Scenario 1) per delivery, potentially alleviating traffic congestion.

The reduction of road VMT due to SADRs has raised concerns about sidewalk congestion, safety, and equity issues such as potential obstructions for disabled individuals (Bennett et al., 2021; Gehrke et al., 2023). Despite these concerns, there have been no recorded SADR collisions with humans to date. According to Gehrke et al. (2023), moderate and dangerous SADR-related conflicts tend to occur in areas with intersecting and narrow pathways lacking clear demarcation for pedestrian space. Survey results indicated that only about 11% of respondents felt uncomfortable sharing pathways with SADRs, reflecting a generally high acceptance of these technologies.

Figure 3. Estimated Change in VMT per Order by Shifting from Robots to Human Delivery

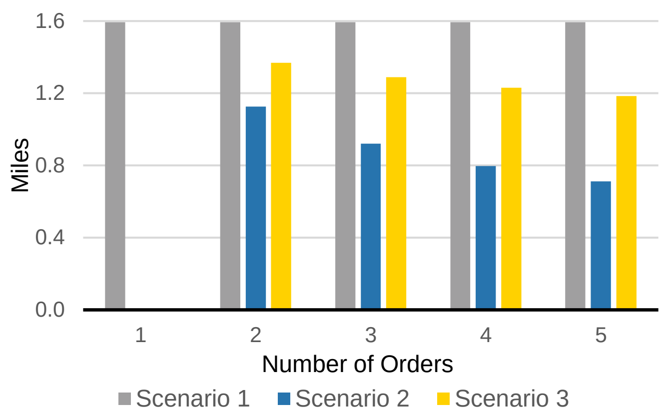
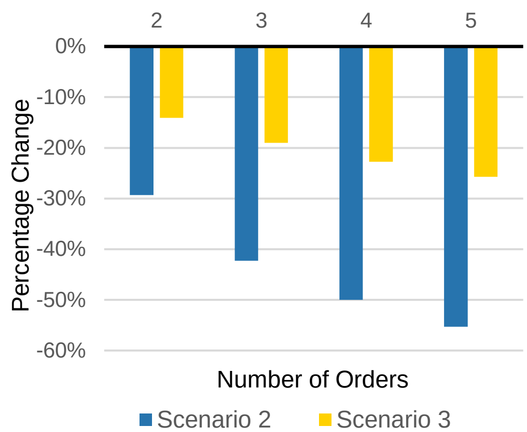


Figure 4. Estimated VMT Reduction Rate per Order by Shifting from Robots to Human Delivery



4.2. Emission Modeling Results

4.2.1. Emission Rates per Mile

The total emission rates, including tailpipe emissions and electricity generation from the EMFAC2021, eGRID datasets, and data provided by Coco Delivery, are detailed in **Table 5** and **Figure 5** to **Figure 11**. A comparison of these emissions is presented in **Table 6**. Estimated emission rates per mile varied significantly across different vehicle categories and fuel types. Generally, cars with gasoline/diesel fuel and motorcycles with gasoline were the most polluting across all emissions categories. However, their rankings varied depending on the types of emissions.

For CO_2, CO_2e, and SO_x emissions, cars fueled by gasoline were the most polluting (612.66 g/mi for CO_2; 615.54 g/mi for CO_2e; 0.0061 g/mi for SO_x), followed by diesel vehicles (565.02 g/mi for CO2; 591.85 g/mi for CO_2e; 0.0054 g/mi for SO_x) and gasoline motorcycles (410.23 g/mi for CO_2; 445.03 g/mi for CO_2e; 0.0041 g/mi for SO_x). Diesel cars emitted the most N_2O (0.089 g/mi) and $PM_{2.5}$ (0.091 g/mi), followed by gasoline motorcycles (0.058 g/mi for N_2O; 0.013 g/mi for $PM_{2.5}$) and gasoline cars (0.009 g/mi for N_2O; 0.009 g/mi for $PM_{2.5}$). Motorcycles with gasoline as the fuel type emitted the most CH_4 (0.697 g/mi) and NO_x (0.804 g/mi), followed by diesel cars (0.012 g/mi for CH_4; 0.314 g/mi for NO_x), and gasoline cars (0.013 g/mi for CH_4; 0.081 g/mi for NO_x).

Hybrid and electric cars generally emitted much fewer pollutants compared to vehicles powered by non-renewable energy sources. Nonetheless, they still produced significantly more emissions than SADRs. As shown in **Table 6**, even hybrid and electric vehicles, which are comparatively clean, still generated 7 to 16 times more emissions per mile than SADRs. Emission rates for non-renewable fuel vehicles exceeded those of SADRs by over a hundred and even more than 1000 times, depending on the types of emissions. This suggests that considering the same delivery distance, SADRs are substantially cleaner and more sustainable than any other vehicle types.

Table 5. Total Emission Rates per Mile Across Different Vehicle Types

VEHICLE TYPE	FUEL TYPE	CO_2	CH_4	N_2O	CO_2e	NO_x	SO_x	$PM_{2.5}$
SADR	Electricity	*9.3*	*0.000531*	*0.000061*	*9.3*	*0.008226*	*0.000306*	*0.000427*
Motorcycle	Gas	410.2	**0.696711**	0.058331	445	**0.803826**	0.004056	0.013104
Car	Gas	**612.7**	0.01327	0.008569	**615.5**	0.080955	**0.006057**	0.008971
	Diesel	565	0.012262	**0.089019**	591.9	0.313801	0.005354	**0.090769**
	Hybrid	154.5	0.004378	0.000873	154.9	0.060684	0.003046	0.004800
	Electricity	96.9	0.005527	0.000638	97.3	0.085676	0.003189	0.005352

*Note: Highest output noted in **bold**, and lowest output in italics.*
Unit: g per mile

Table 6. Comparison of Total Emission Rates per Mile Across Different Vehicle Types and SADRs

VEHICLE TYPE	FUEL TYPE	CO_2	CH_4	N_2O	CO_2e	NO_x	SO_x	$PM_{2.5}$
SADR	Electricity	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*
Motorcycle	Gas	44.1	**1312.8**	952.6	47.7	**97.7**	13.2	30.7
Car	Gas	**65.8**	25.0	139.9	**65.9**	9.8	**19.8**	21.0
Car	Diesel	60.7	23.1	**1453.7**	63.4	38.1	17.5	**212.6**
Car	Hybrid	16.6	8.2	14.3	16.6	7.4	9.9	11.2
Car	Electricity	10.4	10.4	10.4	10.4	10.4	10.4	12.5

*Note: Highest output noted in **bold**, and lowest output in italics*

Figure 5. CO_2 per Mile by Vehicle Type

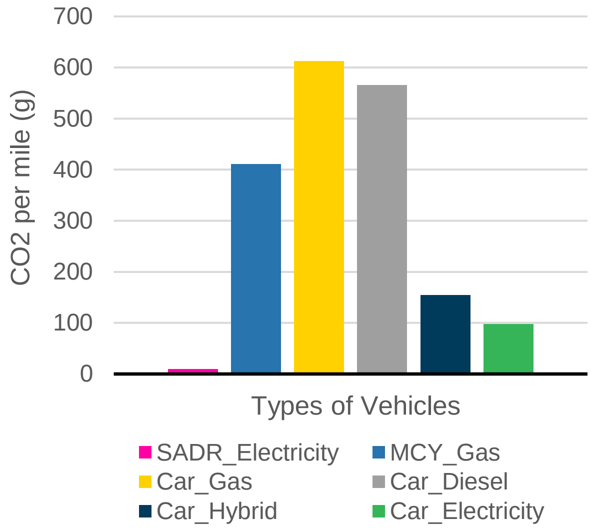


Figure 6. CH_4 per Mile by Vehicle Type

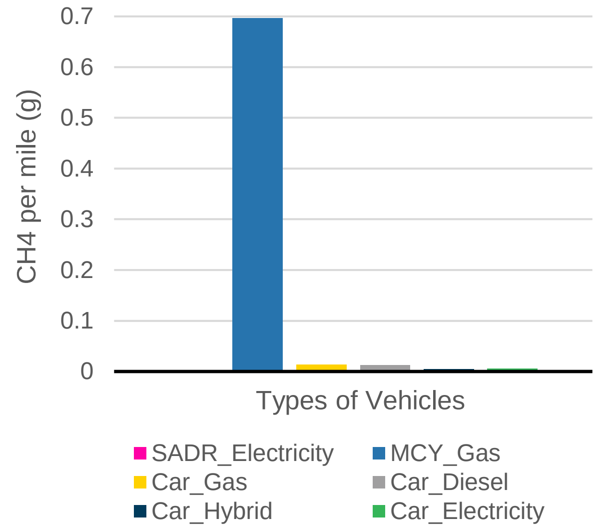


Figure 7. N_2O per Mile by Vehicle Type

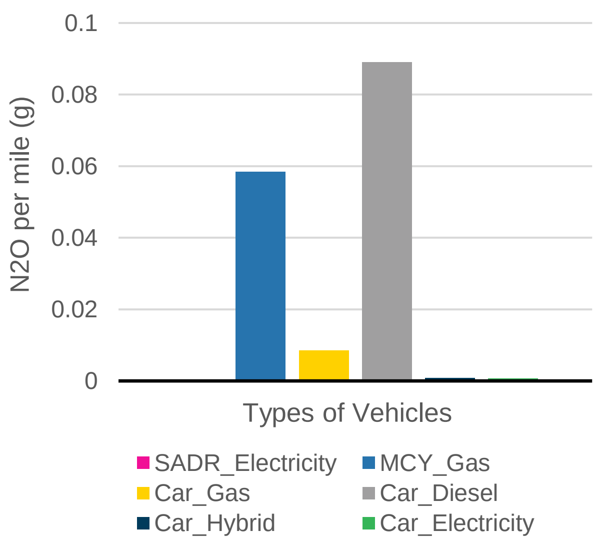


Figure 8. CO_2e per Mile by Vehicle Type

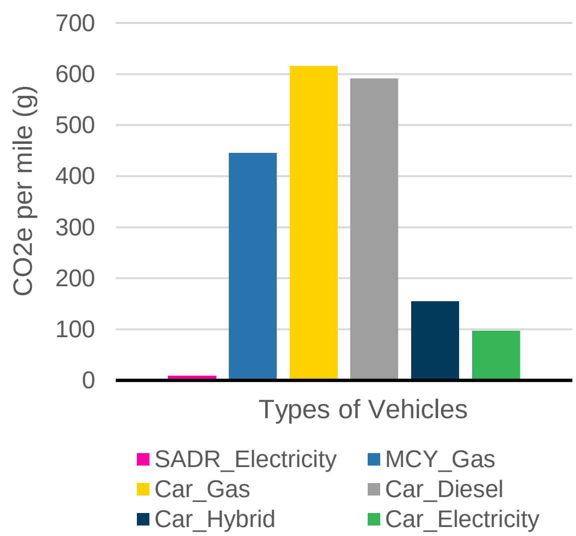


Figure 9. NO_x per Mile by Vehicle Type

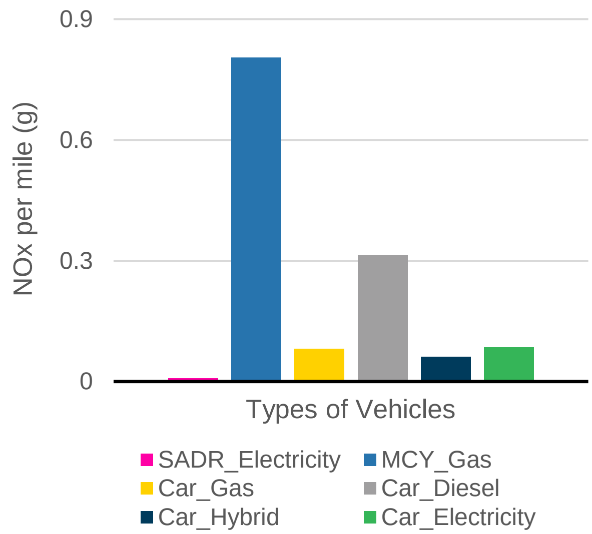


Figure 10. SO_x per Mile by Vehicle Type

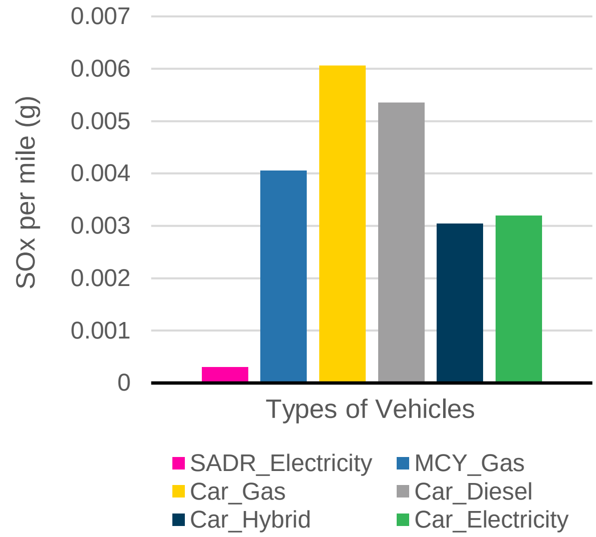
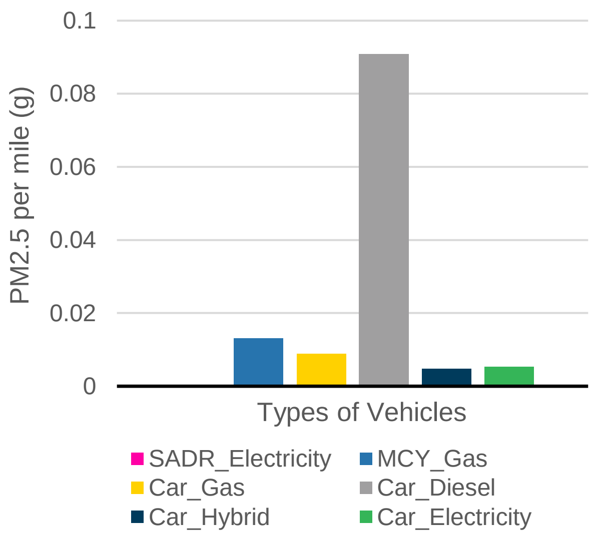


Figure 11. $PM_{2.5}$ per Mile by Vehicle Type



4.2.2. Emission Rates across Different Scenarios

Emission rates per mile differed significantly across various vehicle and fuel types. Notably, SADRs were the most sustainable option for covering the same delivery distances. However, it is important to note that each vehicle type has its capacity limitations, making some scenarios not applicable to certain vehicle types. Specifically, while all conventional human-operated vehicles have larger delivery capacities for batched deliveries (Scenario 2 and Scenario 3), SADRs are typically restricted to one-to-one deliveries (Scenario 1). Their inability to execute batched deliveries narrows the emission disparities between SADRs and other vehicle types for some delivery scenarios.

I assumed that a delivery driver handled between three to five orders in a single delivery tour. The emissions for different vehicle types across the scenarios of three and five orders are detailed in **Table 7** and **Figure 12** to **Figure 18**, while comparisons with SADRs are provided in **Table 8**. When performing batched deliveries with three orders, the relative emissions from gasoline and diesel vehicles—ranging from five times (NO_x from gasoline cars) to over 800 times (N_2O from diesel cars) greater than SADRs in Scenario 2, and from eight to over a thousand times in Scenario 3—demonstrated the significant emissions benefits of SADRs. Electric and hybrid human-driven vehicles performed comparatively better, with emissions ranging from four to ten times greater than SADRs in Scenario 2, and from six to thirteen times in Scenario 3.

Unsurprisingly, the emissions gap narrowed as the number of orders per trip increased. For trips involving five orders, gasoline-powered and diesel-powered vehicles ranged from four to 650 times the emissions of SADRs in Scenario 2, and from seven to over a thousand times in Scenario 3. Conversely, electric and hybrid vehicles emitted three to seven times SADR emissions in Scenario 2, and five to 12 times the emissions for Scenario 3.

Despite the significant reductions in emissions achievable through batched human deliveries, SADRs consistently exhibited the lowest emissions across all vehicle and fuel types. Moreover, the likelihood of a delivery driver managing more than three orders per trip (without delivering to the same locations) is quite low. Therefore, SADRs remain the most sustainable choice in the on-demand and small-scale food delivery industry.

Table 7. Emissions per Order for Different Vehicles and Fuel Types on 3- and 5-Order Trips

		VEHICLE TYPE	FUEL TYPE	CO_2	CH_4	N_2O	CO_2e	NO_x	SO_x	$PM_{2.5}$
	Scenario 1	SADR	Electricity	*14.83*	*0.000846*	*0.000098*	*14.88*	*0.013107*	*0.000488*	*0.00068*
		Motorcycle	Gas	653.63	**1.110099**	0.092941	709.08	**1.28077**	0.006462	0.02088
		Car	Gas	**976.17**	0.021144	0.013654	**980.77**	0.128989	**0.00965**	0.014293
			Diesel	900.26	0.019538	**0.141837**	943.02	0.499992	0.00853	**0.144627**
			Hybrid	246.23	0.006976	0.001391	246.82	0.09669	0.004853	0.007648
			Electricity	154.44	0.008807	0.001016	154.97	0.136512	0.005081	0.008527
3 Orders	Scenario 2	Motorcycle	Gas	377.38	**0.640916**	0.05366	409.39	**0.739453**	0.003731	0.012055
		Car	Gas	**563.59**	0.012207	0.007883	**566.25**	0.074472	**0.005572**	0.008252
			Diesel	519.77	0.01128	**0.08189**	544.45	0.288671	0.004925	**0.0835**
			Hybrid	142.16	0.004028	0.000803	142.50	0.055824	0.002802	0.004416
			Electricity	89.17	0.005085	0.000587	89.47	0.078815	0.002934	0.004923
	Scenario 3	Motorcycle	Gas	529.16	**0.8987**	0.075242	574.05	**1.036869**	0.005231	0.016904
		Car	Gas	**790.28**	0.017117	0.011054	**794.00**	0.104425	**0.007813**	0.011571
			Diesel	728.82	0.015817	**0.114827**	763.44	0.404777	0.006906	**0.117085**
			Hybrid	199.34	0.005647	0.001126	199.82	0.078277	0.003928	0.006192
			Electricity	125.03	0.00713	0.000823	125.46	0.110515	0.004113	0.006904
5 Orders	Scenario 2	Motorcycle	Gas	292.31	**0.496451**	0.041565	317.11	**0.572778**	0.00289	0.009338
		Car	Gas	**436.56**	0.009456	0.006106	**438.61**	0.057686	**0.004316**	0.006392
			Diesel	402.61	0.008738	**0.063431**	421.73	0.223603	0.003815	**0.064679**
			Hybrid	110.12	0.00312	0.000622	110.38	0.043241	0.00217	0.00342
			Electricity	69.07	0.003939	0.000454	69.30	0.06105	0.002272	0.003814
	Scenario 3	Motorcycle	Gas	485.70	**0.824887**	0.069062	526.90	**0.951708**	0.004802	0.015515
		Car	Gas	**725.37**	0.015712	0.010146	**728.79**	0.095848	**0.007171**	0.010621
			Diesel	668.96	0.014518	**0.105396**	700.73	0.371532	0.006339	**0.107468**
			Hybrid	182.97	0.005184	0.001034	183.40	0.071848	0.003606	0.005683
			Electricity	114.76	0.006544	0.000755	115.15	0.101438	0.003776	0.006337

*Note: Highest output noted in **bold** in each scenario, and lowest output in italics.*
Unit: g per mile

Table 8. Emission Comparisons for Various Vehicles and Fuel Types on 3- and 5-Order Trips

		VEHICLE TYPE	FUEL TYPE	CO_2	CH_4	N_2O	CO_2e	NO_x	SO_x	$PM_{2.5}$
	Scenario 1	SADR	Electricity	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*
		Motorcycle	Gas	44.1	**1312.8**	952.6	47.7	**97.7**	13.2	30.7
		Car	Gas	**65.8**	25.0	139.9	**65.9**	9.8	**19.8**	21.0
			Diesel	60.7	23.1	**1453.7**	63.4	38.1	17.5	**212.6**
			Hybrid	16.6	8.2	14.3	16.6	7.4	9.9	11.2
			Electricity	10.4	10.4	10.4	10.4	10.4	10.4	12.5
3 Orders	Scenario 2	Motorcycle	Gas	25.4	**757.9**	550.0	27.5	**56.4**	7.6	17.7
		Car	Gas	**38.0**	14.4	80.8	**38.1**	5.7	**11.4**	12.1
			Diesel	35.1	13.3	**839.3**	36.6	22.0	10.1	**122.7**
			Hybrid	9.6	4.8	8.2	9.6	4.3	5.7	6.5
			Electricity	6.0	6.0	6.0	6.0	6.0	6.0	7.2
	Scenario 3	Motorcycle	Gas	35.7	**1062.8**	771.2	38.6	**79.1**	10.7	24.8
		Car	Gas	**53.3**	20.2	113.3	**53.4**	8.0	**16.0**	17.0
			Diesel	49.1	18.7	**1176.9**	51.3	30.9	14.2	**172.1**
			Hybrid	13.4	6.7	11.5	13.4	6.0	8.1	9.1
			Electricity	8.4	8.4	8.4	8.4	8.4	8.4	10.1
5 Orders	Scenario 2	Motorcycle	Gas	19.7	**587.1**	426.0	21.3	**43.7**	5.9	13.7
		Car	Gas	**29.4**	11.2	62.6	**29.5**	4.4	**8.8**	9.4
			Diesel	27.2	10.3	**650.1**	28.3	17.1	7.8	**95.1**
			Hybrid	7.4	3.7	6.4	7.4	3.3	4.4	5.0
			Electricity	4.7	4.7	4.7	4.7	4.7	4.7	5.6
	Scenario 3	Motorcycle	Gas	32.8	**975.5**	707.8	35.4	**72.6**	9.8	22.8
		Car	Gas	**48.9**	18.6	104.0	**49.0**	7.3	**14.7**	15.6
			Diesel	45.1	17.2	**1080.2**	47.1	28.3	13.0	**158.0**
			Hybrid	12.3	6.1	10.6	12.3	5.5	7.4	8.4
			Electricity	7.7	7.7	7.7	7.7	7.7	7.7	9.3

*Note: Highest output noted in **bold** in each scenario, and lowest output in italic*

Figure 12. CO_2 per Order in a 3-Order Delivery Trip

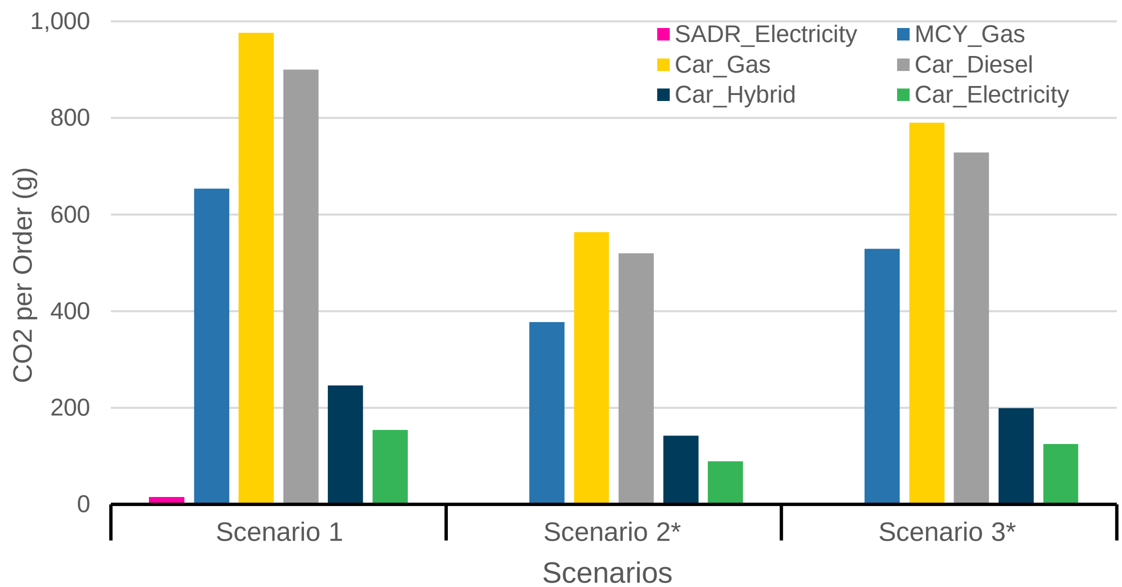
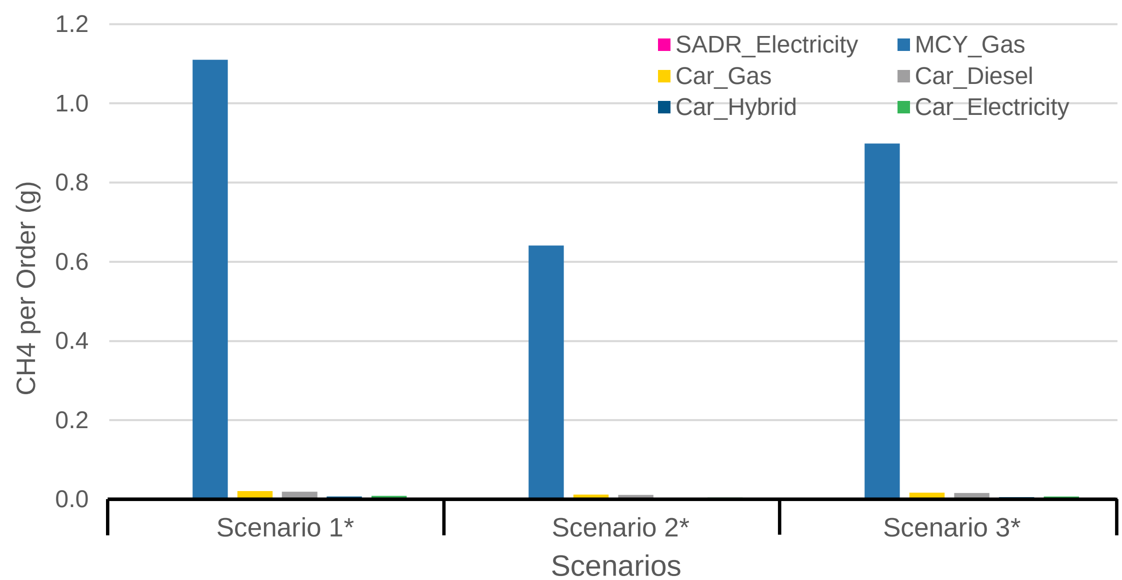


Figure 13. CH_4 per Order in a 3-Order Delivery Trip



**The emission from SADRs in the scenario is too low to be visible in the chart.*

Figure 14. N_2O per Order in a 3-Order Delivery Trip

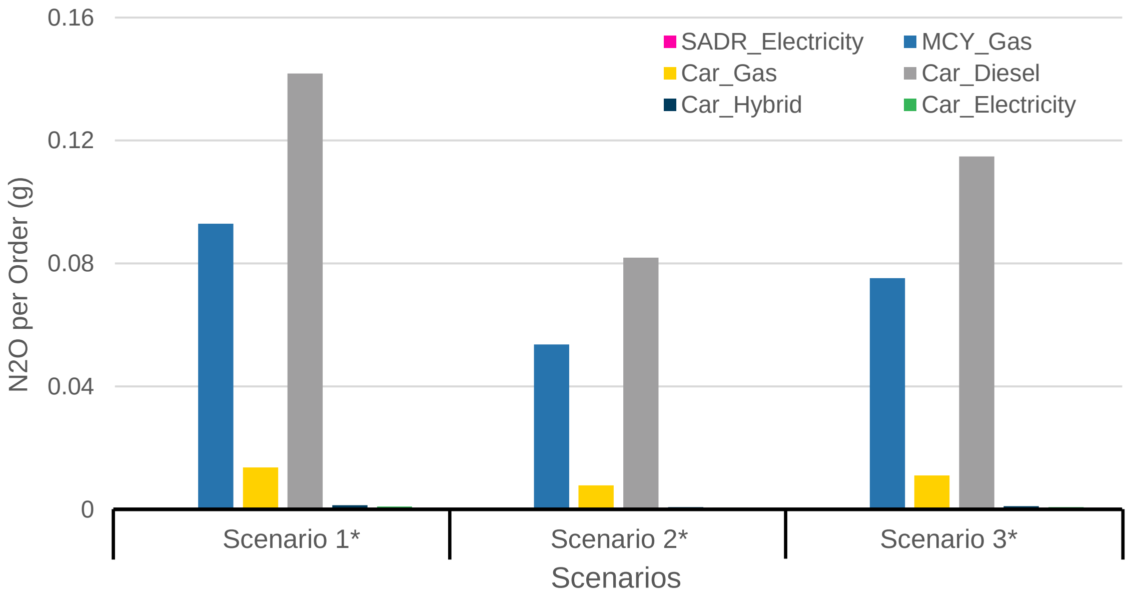
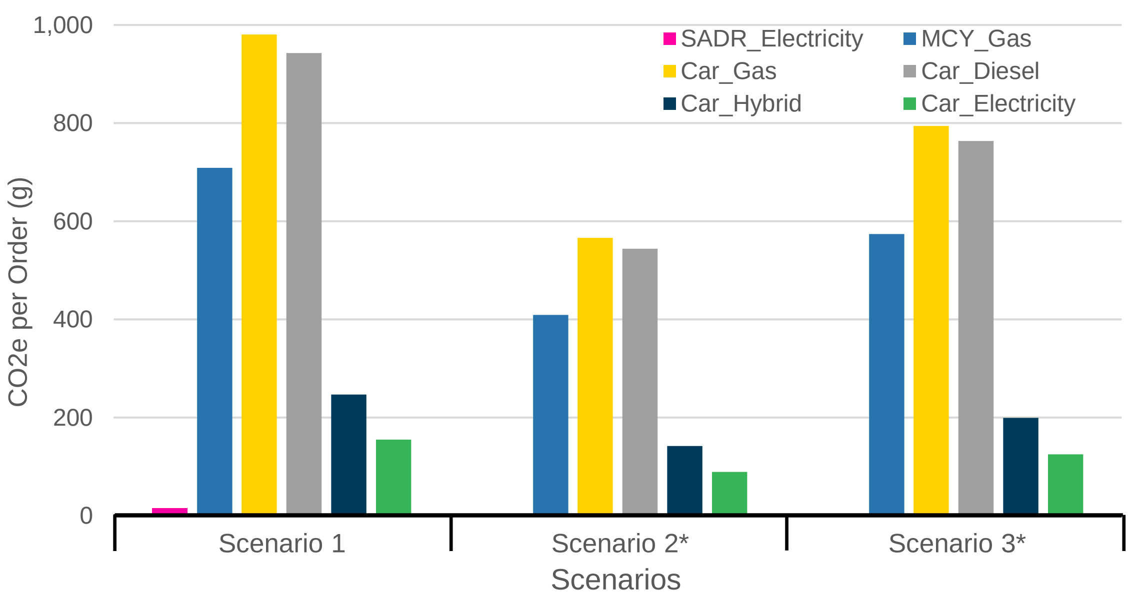


Figure 15. CO_2e per Order in a 3-Order Delivery Trip



**The emission from SADRs in the scenario is too low to be visible in the chart.*

Figure 16. NO_x per Order in a 3-Order Delivery Trip

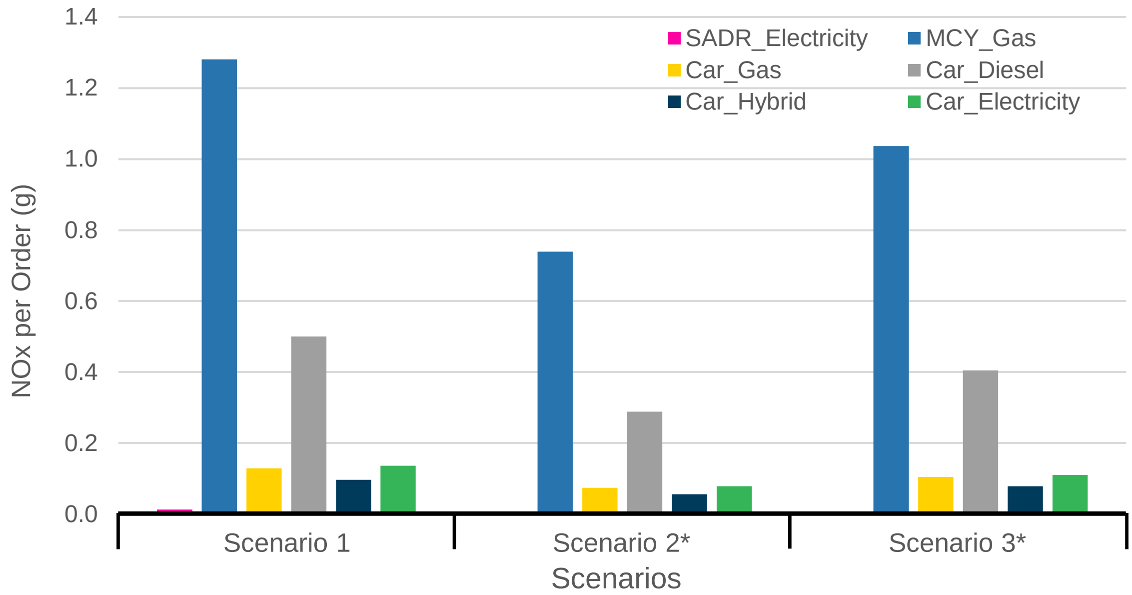
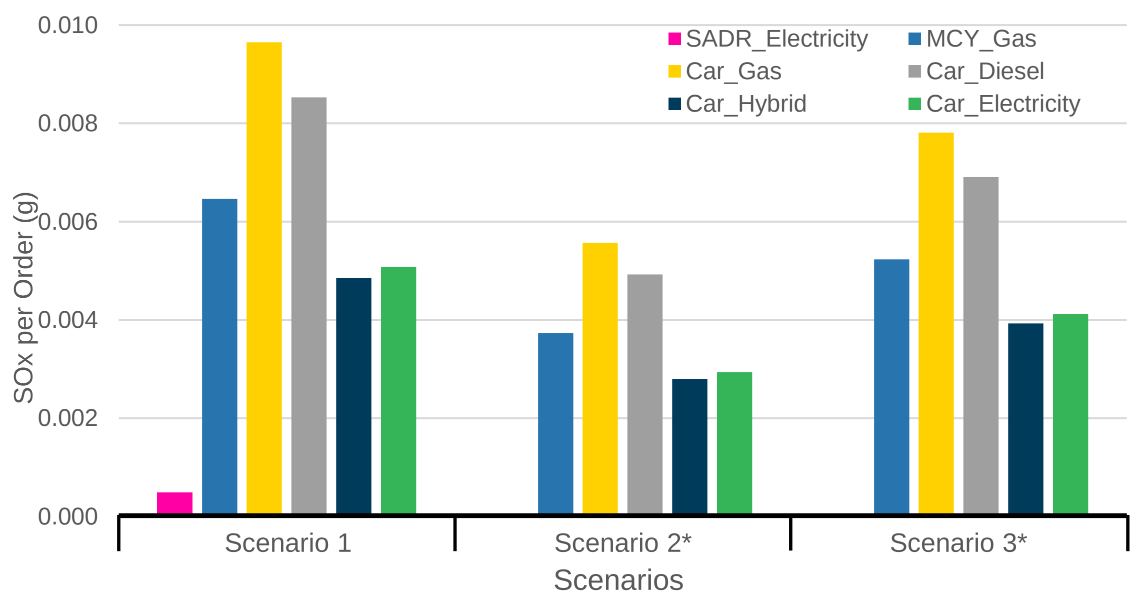
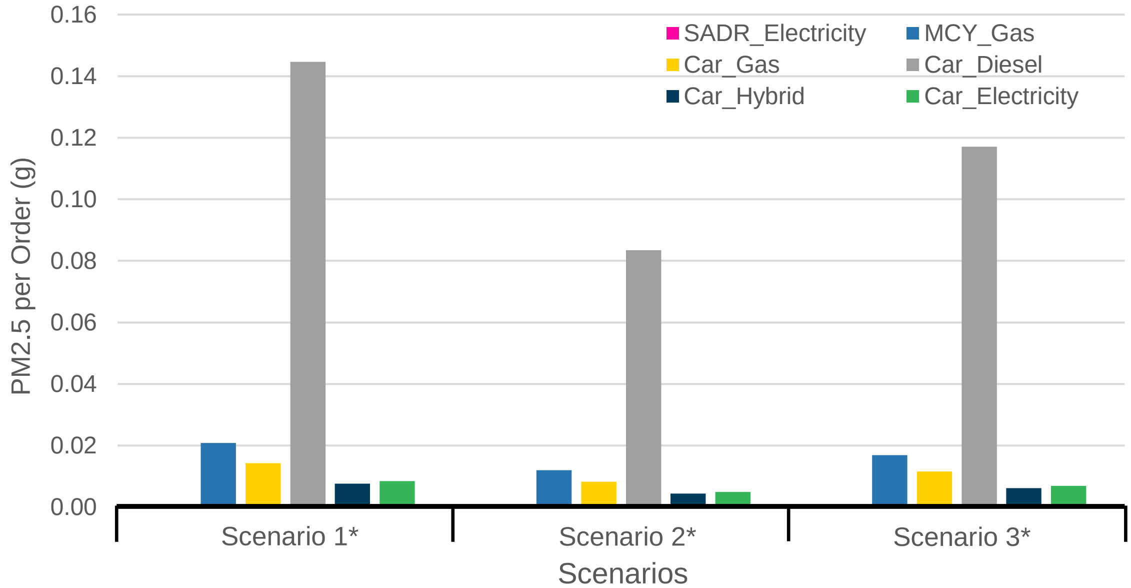


Figure 17. SO_x per Order in a 3-Order Delivery Trip



**The emission from SADRs in the scenario is too low to be visible in the chart.*

Figure 18. $PM_{2.5}$ per Order in a 3-Order Delivery Trip



**The emission from SADRs in the scenario is too low to be visible in the chart.*

5. Policy Recommendations and Conclusion

5.1. Policy Recommendations

SADRs have emerged as viable last-mile delivery technologies post-COVID-19. They offer benefits like lower emissions, cost-effectiveness, and contactless service. However, their adoption is limited by the requirement for high-quality, expansive sidewalks, which many cities lack. Moreover, they have not been significantly recognized by most governments as a potentially effective means to alleviate traffic congestion and reduce greenhouse gas emissions. Given these research findings, I propose the following recommendations:

1. Promote SADR Adoption

Local, regional, and even state governments should consider SADRs as strategic solutions to reduce traffic congestion and emissions. Many states lack legislation supporting SADRs, hindering their widespread use. Promoting their adoption in dense urban areas can replace conventional delivery vehicles that generate more VMT and emissions per delivery.

2. Develop SADR-friendly Sidewalk Infrastructure

Given the typical state of US city sidewalks, there is a need for improvement to encourage walking, improve access for the elderly and disabled, and to accommodate SADRs. Such development will not only help to prevent sidewalk congestion but also enhance accessibility for disabled travelers who benefit from similar infrastructure requirements as SADRs, such as wider and barrier-free pathways.

5.2. Conclusion

In this study, I explored the potential of Sidewalk Autonomous Delivery Robots (SADRs) to alleviate traffic congestion and reduce emissions, with a particular focus on on-demand food delivery. By using continuous approximation, EMFAC2021, the eGRID dataset, and SADR data from Coco Delivery, I demonstrated that SADRs generate significantly lower emissions like CO_2, CH_4, N_2O, CO_2e, N_xO, SO_x, and $PM_{2.5}$ compared to conventional human-operated deliver vehicles. For the same delivery distance, SADRs could reduce different types of emissions by 90% to more than 99.9% compared to fuel-based vehicles, and by 86% to 94% compared to electric or hybrid vehicles. In scenarios of batched delivery, SADRs could reduce different types of emissions by 82% to more than 99.9% during a 3-order delivery trip, and by 67% to 99% during a 5-order delivery trip. While the VMT of SADRs was higher than conventional vehicles when batch delivery was considered, the VMT occurred on sidewalks rather than roads, potentially removing 0.7 to 1.59 miles of VMT per order, which would help to mitigate traffic congestion. However, the reduction of road VMT by SADRs came at the cost of increased sidewalk usage, which could lead to congestion and reduced accessibility for disabled individuals amidst widespread adoption.

To ensure a balance between reducing road traffic and emissions and maintaining pedestrian equity and safety, I recommend that governments legislate support for the adoption of SADRs to improve traffic conditions, air quality, and greenhouse gas (GHG) emissions reductions. Additionally, developing sidewalk infrastructure that accommodates SADRs alongside traditional transportation systems will support sustainable technologies and create an inclusive environment for all.

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