Modeling Eco-Routing and Congestion Zone Impacts on Vehicular CO_2 Emissions in Washington, D.C.

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Abstract:

Mitigating vehicular carbon emissions remains a critical focus for efforts at combatting climate change. Using the Washington, D.C. area as a case study, this paper investigates potential reductions in vehicular carbon emissions through the complete adoption of eco-routing—the selection of vehicle paths that optimize for fuel consumption rather than travel time. Additionally, we examine the environmental and travel-time impacts of implementing a congestion pricing zone in the center of Washington, D.C. Vehicles were simulated using the Simulation of Urban MObility (SUMO) platform to analyze the effects of these traffic interventions on vehicular carbon emissions and average travel times in the Washington, D.C. area. Analysis of 480 simulations revealed that eco-routing reduced CO_2 emissions by up to 23% during peak times in comparison to time-optimized routing, but also increased average trip times by 12-18% in comparison. Furthermore, testing indicated that the addition of a congestion zone policy in the D.C. Central Business District can reduce carbon emissions by up to 7.4% during peak times. However, the congestion zone was only effective during busy hours, and combining the congestion zone with eco-routing eliminated the zone's benefit–slightly increasing emissions relative to eco-routing alone, as both interventions divert vehicles onto smaller roads and interfere when applied together. Our findings underscore that carbon-optimized routing and traffic policy interventions can achieve substantial reductions in vehicular CO_2 emissions within urban networks, at the expense of slightly longer travel times.

Keywords:
Eco-Routing, Congestion pricing, Emission modeling, Transportation policy, Vehicular CO_2 emissions, Washington, D.C., Urban traffic simulation, Carbon emission reduction, SUMO (Simulation of Urban MObility), Sustainable transportation, Greenhouse gas mitigation, Traffic microsimulation

1. Introduction

Climate change continues to be an area of frequent discussion among the scientific community, having been featured in the Global Risks Report for the past two decades [1]. The implications of climate change are ubiquitous: consequences include elevated sea levels, increased frequency of extreme weather events, and biodiversity/habitat loss [2]. Primarily driving the climate crisis are anthropogenic greenhouse gas emissions from the combustion of fossil fuels. In 2025, the transportation industry alone accounted for approximately 28% of greenhouse gas emissions within the United States, of which 57% is attributable to road vehicles [3][4]. As 97% of road vehicles run on gasoline, mitigating vehicular carbon emissions remains a national and global priority [4]. One method of mitigating high levels of vehicular carbon emissions is through the use of eco-routing. Eco-routing refers to the selection of vehicle routes that optimize for fuel consumption and carbon emissions rather than travel time, often considering variables such as traffic conditions, elevation, and travel speed to minimize fuel usage [5][6]. Eco-routing is beneficial for the environment because it can significantly reduce fuel expenditure and thus CO_2 emissions: one study analyzing areas of Lisbon, Portugal, indicated eco-routing reduced emissions by up to 20% overall, at the expense of slightly longer travel duration [7]. However, no research has been done specifically for the Washington, D.C. area—the city with the highest average daily commute times in America [8]. And while eco-optimized routes occasionally appear as an option in navigation apps such as Google Maps, it is not universally used by all. Therefore, to have a deeper understanding of the full potential benefits of eco-routing applied to Washington D.C., this paper analyzes the extent to which the total adoption of eco-routing can reduce CO_2 emissions and traffic congestion within D.C.—if at all. Additionally, another strategy that has shown merit in mitigating vehicular carbon emissions is congestion zone pricing. By imposing fees on drivers entering central areas of high demand, congestion zones alleviate congestion in high-demand urban areas, cut vehicular carbon emissions, and generate government revenue as a side effect [9]. For example, an established congestion policy in the Central Business Zone in New York was estimated to decrease carbon emissions by ~7-18% [9]. However, little research has specifically examined these effects if a zone was added to Washington, D.C. Thus, in addition to eco-routing, we investigate the environmental benefits—if any—that implementing a similar congestion zone policy could bring to Washington, D.C. While both eco-routing and congestion zones have been investigated independently within large-scale urban networks, to our knowledge, limited research has examined both techniques working simultaneously within a single urban network. Therefore, we explore the effects of eco-routing and congestion zones working in isolation and working in tandem. Our study aims to reveal whether their combined implementation introduces complementary benefits, trade-offs, or unintended consequences in reducing congestion and vehicular CO_2 emissions in the D.C. area.

2. Methods

2.1 Road Network

First, a network of roads was needed to run simulations for the Washington, D.C. area. The District of Columbia's urban area and traffic patterns are closely linked with areas of Northern Virginia to the west of the District, so our network is made up of the District of Columbia along with portions of the neighboring counties of Arlington and Alexandria to complete a traffic network. All road data for these areas was extracted from OpenStreetMap [10], using the District of Columbia's three vertices to form a diamond-shaped network. The full simulation network encapsulates 47,331 edges, which we take to be an approximation for the traffic network of the Washington, D.C. area. From OpenStreetMap, each network edge stores information such as length, elevation, number of lanes, directionality, speed limits, traffic lights, and turning lanes [10]. All of these parameters are factored in during simulations to calculate estimated travel time and CO_2 emissions. Vehicles automatically adapt to the speed limits, distances, and other observed road factors within the network. Additionally, the road network was filtered to include only the data and edges that were relevant for cars, so information specific to pedestrians and bikes was removed. The final network was uploaded to and rendered in the Simulation of Urban MObility (SUO) [11].

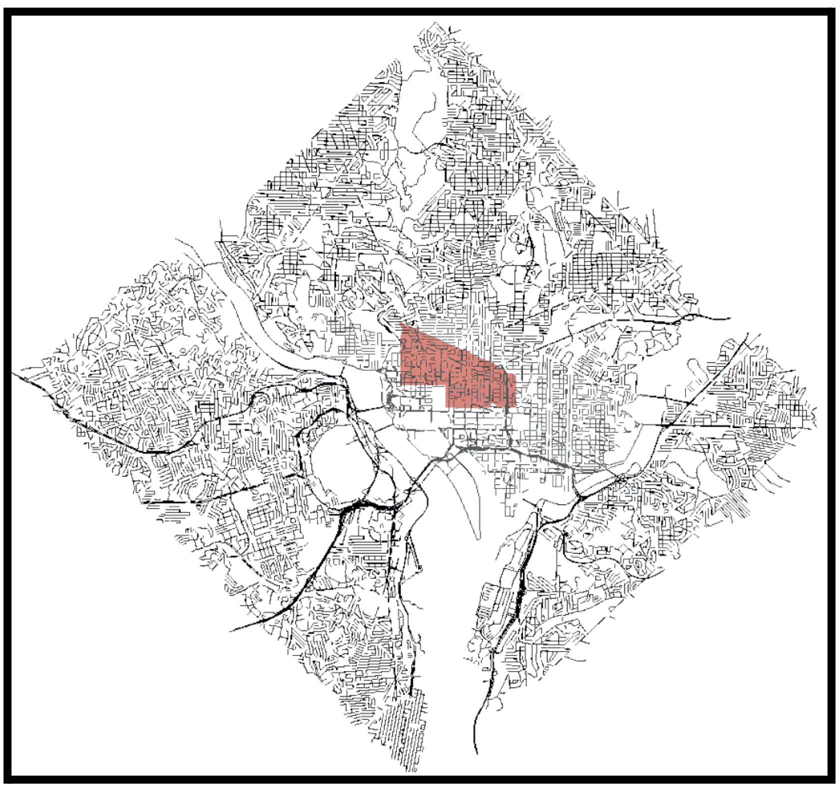

Figure 1. A screenshot of the full road network in SUMO, comprising road data from the District of Columbia, Arlington County, and Alexandria County. The simulated congestion zone in the D.C. Central Business District is shown in red.

2.2 Congestion Zone

The general aim of an urban congestion zone is to reduce traffic by redirecting vehicles around the traffic-heavy city core, which distributes traffic more evenly throughout the region. Successful congestion policies have been implemented in cities like New York City, London, and Stockholm, each demonstrating a reduction in congestion and traffic volume [12][13][14]. For our simulation of the Washington, D.C. area, we defined the congestion policy zone to be D.C.'s Central Business District, as it is considered a traffic-heavy region in the city core [15]. To simulate a zone entrance fee that redirects traffic away from the Central Business District, the congestion zone can be assigned a customizable access rate parameter from 0-100%, which determines the percentage of cars needing the zone that are allowed to enter. For example, an access rate of 70% means for every 100 cars that would otherwise pass through the zone, 30 of them must be redirected around, and the other 70 are allowed through. Vehicles that start or end inside of the zone are always allowed through. Although using a constant access percentage to model a congestion fee doesn't account for individual driver intent (in reality, whether or not a car chooses to enter the zone is a matter of human behavior), the objective of our zone experiments is to compare how overall traffic conditions and CO_2 emissions change under different routing conditions. The access rate instead approximates the aggregate outcomes of fee pricing and individual driver decisions, and in effect, can be used to tune the efficiency of the congestion zone fee without needing to account for human decision-making, making it an appropriate measure for this study. Determining an appropriate fee price to match these access rates, however, remains a subject for future research. Therefore, this study tests simulations with varying access rates of 70%, 80%, 90% to analyze how the efficiency of the simulated congestion zone policy changed overall CO_2 emissions, if at all. Access percentages at or below 60% were not tested because they are inefficient for real-world congestion zone policies: successful congestion zones around the world demonstrate much higher equivalent zone access rates; examples include London (82%) [13], Stockholm (80%) [14], and New York City (89%) [12].

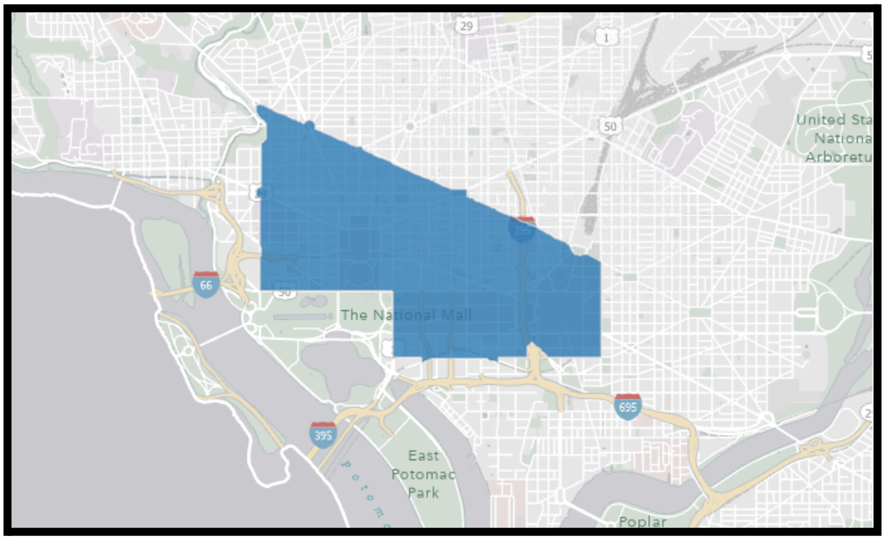

Figure 2. D.C.'s Central Business District, used as the boundary for the simulated congestion pricing zone. Adapted from Open Data DC [15], CC BY 4.0.

2.3 Simulation Structure

To design and run simulations, we utilize the Simulation of Urban MObility (SUMO), a microscopic, multi-modal traffic simulator software [11]. SUMO creates models of traffic scenarios where individual vehicles move through a given road network, allowing for novel traffic systems to be tested under varying circumstances. Each vehicle is modeled explicitly, has a unique route, obeys traffic rules, and moves individually through the network [11]. Simulations are inherently deterministic, but randomness is introduced through seed-generated origin-destination paths. The simulation itself has space-continuous and time-discrete vehicle movement, different vehicle types, multi-lane streets, traffic lights, and even person-based inter-modal trips [11].

To model the effects of fastest-routing vs. eco-routing in the Washington, D.C. area as well the impacts of a potential central congestion zone charge, simulations were run in groups of 4 sub-cases of conditions applied:

(i) Case 1: Fastest-routing only

(ii) Case 2: Eco-routing only

(iii) Case 3: Fastest-routing with congestion zone

(iv) Case 4: Eco-routing with congestion zone

This setup of four cases per set of simulation parameters allows us to isolate how the eco-routing and congestion zone affect carbon emissions independently, as well as how routing affects carbon emissions when used in tandem with a congestion zone. Throughout each group of 4 runs, each case uses the same number of cars and the same origin-destination pairs for route generation to maintain consistency. Simulations are also structured to account for the wide variations in D.C. traffic patterns seen throughout the day. In order to analyze traffic throughout

the whole day with regard to congestion zones and eco-routing, all simulations are repeated across four different divisions of the day:
(i) Off-Hours: represents light, off-hour traffic *(7pm - 6am)*
(ii) AM Rush: represents morning rush-hour traffic *(6am - 9am)*
(iii) Midday: represents midday traffic *(9am - 3pm)*
(iv) PM Rush: represents afternoon rush-hour traffic *(3pm - 7pm)*
Each of these time periods represents a unique volume of cars with unique driving patterns based on real-world data. The precise workings of the time periods are explained in further detail in sections 2.4.2 and 2.4.3. Overall, using representative time intervals allows for holistic analysis of eco-routing and congestion zones on D.C. traffic, rather than modeling over a single time period.

2.4 Route Generation
Many factors are taken into account to ensure reasonably accurate vehicular route generation. The simulation first creates a file which contains origin-destination pairs for an inputted number of trips per hour. The rationale for trip counts can be found in 2.4.3. These origin-destination pairs are generated randomly, but are given spatial bias throughout the network to match regional trends in traffic patterns throughout different times of day. See 2.4.2 for more details on this. Then, the routes are further biased to match real-world trip distances. Data from the Bureau of Transportation Statistics indicates that average one-way household trips in D.C. were ~6-7 miles long in 2022 [16]. We were unable to locate trip length data specifically for D.C., but the national estimate seemed reasonable to adopt for our simulation, as our road network fits the scale, and it reasonably matched other sources. Therefore, in order for each route to be approximately 7 miles long, a rejection-sampling loop was used to bias origin-destination generation until the average trip length reasonably approached ~7 miles. Finally, once the routes were appropriately biased for location and length, these origin-destination pairs were converted into full routes across the network using a tool called DuaRouter, using either an eco-routing or fastest-routing algorithm. This step is further explained in 2.4.1.

2.4.1 *DuaRouter for the Four Cases*
DuaRouter is a tool included within SUMO, which is designed to generate routes under different conditions. Given origin-destination pairs and a road network, DuaRouter automatically generates routes according to the specified type of routing algorithm [11].
(i) Fastest-routing Simulations: DuaRouter chooses the route with the lowest time spent travelling. It assigns weights to edges on the network based on each edge's predicted travel time, which is calculated using SUMO's built-in vehicle timing algorithm. Using these weights, DuaRouter applies Dijkstra's algorithm to the road network to determine each car's fastest path between their predetermined origin and destination points [11].
(ii) Eco-routing Simulations: DuaRouter chooses the route with the lowest projected CO_2 emissions. Emissions are predicted using the emission class HBEFA4/PC_petrol_Euro-6d,

which DuaRouter uses to simulate emitted CO_2 based on factors including speed, elevation change, acceleration, traffic, and vehicle type [11]. All vehicles are assumed to use internal combustion engines whose CO_2 emissions are measured using Euro-6d emission standards, an approximation that aligns with the EPA CO_2 emission standards of many new cars frequently found in America [11]. Similarly to fastest-routing, projected CO_2 measurements are used as weights for all edges of the network, and Dijkstra's algorithm is again applied to determine the most eco-efficient route for each car [11].

(iii) Routing with a Congestion Zone: For simulations that use a congestion zone, a certain proportion of vehicles, as defined by the zone access rate, calculate their routes using a separate network with all edges of the congestion zone completely removed. This simulates cars taking detours as a result of the congestion zone. If a vehicle's origin or destination lies inside the congestion zone, then they switch to using the complete network, essentially being "forced" in.

(iv) Dynamic Rerouting: In any case, as simulations run, each vehicle reruns its respective routing algorithm every 60 seconds, taking into account current traffic conditions [11]. This allows cars to adapt their routes dynamically in response to current congestion, similar to how real-world navigation apps account for real-time traffic.

2.4.2 *Route Origin-Destination Bias*

Further, the origin-destination points of trip generation are matched to real-world regional traffic trends in the D.C. area. For example, during the PM rush hour, vehicles are more frequently leaving D.C. from the core (offices) to go to the suburbs (homes) than vice versa. In order to bias route generation to account for such regional trends, we divided our road network into three subdivisions and gave each subdivision an appropriate weight to bias origins and destinations depending on the time of day. Our three traffic-analysis divisions are diamond-shaped and appear as such: an inner division representing the main urban area, a middle division representing homes and businesses, and an outer division representing commuters. A figure is shown below.

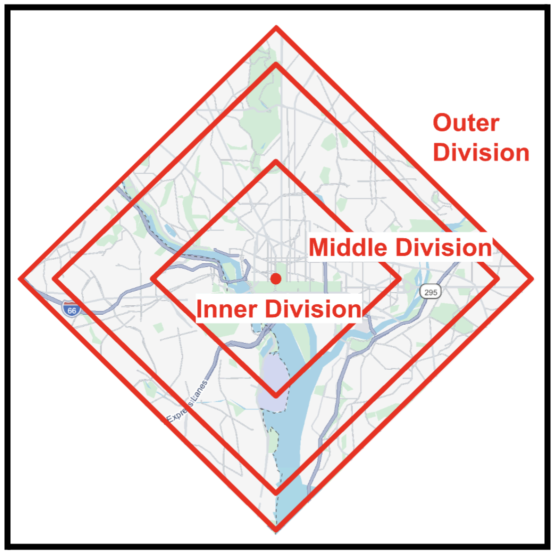

Figure 3. Visual representation of the three traffic-analysis divisions used to bias origin-destination points for vehicle routes. The inner division border radius (distance from center to vertex) is 3.5 mi, and the middle division border radius is 6.7 mi. Background imagery © Google Earth.

Using these three subdivisions, we were able to roughly simulate route trends throughout the day that would more realistically model regional D.C. traffic flows. Using information from the Washington, DC Household Survey Key Findings [17] and 2022 National Household Survey conducted by the Federal Highway Administration [18], we obtained the following data according to the varying time periods and network regions.

Table 1. Percent distribution of route origins and destinations across the three traffic-analysis divisions (Inner, Middle, Outer) for each time frame. Distributions are based on data from the Washington, DC Household Survey Key Findings [16] and the 2022 National Household Travel Survey [17]. AM Rush traffic flows predominantly from outer regions toward the city center; PM Rush flows outward from the center; Midday and Off-Hours traffic occurs bidirectionally with no net regional change.

Period	Zone	% Origins	% Destinations
AM Rush	Inner	10	35
AM Rush	Middle	35	55
AM Rush	Outer	55	10
Midday	Inner	20	20

Midday	Middle	60	60
Midday	Outer	20	20
Off-Hours	Inner	15	15
Off-Hours	Middle	75	75
Off-Hours	Outer	10	10
PM Rush	Inner	30	10
PM Rush	Middle	65	45
PM Rush	Outer	5	45

2.4.3 *Calculating Hourly Trip Counts*

Regardless of how vehicle routes are distributed, Washington, D.C. experiences widely varying levels of traffic influx throughout the day. To account for this fact, we calculated different vehicle counts to simulate over our four time frames of: Off-hours, AM rush, Midday, and PM rush. Since these vehicle counts include commuters entering the D.C. area from external areas, we based our calculations on road network statistics for D.C. rather than per-capita statistics:

Using annual road volume data from opendata.dc.gov [19], average daily VMT (vehicle miles travelled) for the District of Columbia is **9,987,154.8 miles.**

Given that and a previous approximation that D.C. trips average ~7 miles, we calculate:

$\frac{9{,}987{,}154.8\ total\ miles}{7\ miles\ per\ trip} = \sim 1,427,911\ avg.\ daily\ D.C.\ trips$ (eq1)

To calculate the number of trips made during different times of day, a dataset from the National Capital Region Transportation Planning Board [20] provides percentage distributions of D.C. area traffic across hours of the day. Using this information, we calculated appropriate trip counts for an hour selected to represent each time interval.

(i) (4am - 5am) - 1.76% of daily trips[20] = **~25,131 trips per hour** *(representative of off-hours)*

(ii) (7am - 8am) - 5.81% of daily trips[20] = **~82,962 trips per hour** *(representative of AM rush)*

(iii) (11am - 12pm) - 4.78% of daily trips[20] = **~69,539 trips per hour** *(representative of Midday)*

(iv) (3pm - 4pm) - 5.86% of daily trips[20] = **~83,675 trips per hour** *(representative of PM rush)*

However, this data only accounts for the District of Columbia (D.C.), so we need to expand the numbers to account for the regions in Northern Virginia (NoVA) that are also included in the simulation. Because D.C. and our regions of NoVA have very similar employment density and land usage [21][22], we use the populations of the two areas as a relative proxy for scaling trip counts to estimate a trip count increase from adding NoVA to the simulation area.

(i) Added NoVA area = **32.363083mi^2**;

(ii) D.C. area = **61.1mi^2** [21];

(iii) D.C. population density = **11,280.7 per mi^2** [23];

(iv) Added NoVA population density = **9,375 per mi²** [22]
Using the ratio of D.C. population to full simulation population:

$$\frac{D.C.\,area \cdot D.C.\,pop.\,density}{D.C.\,area \cdot D.C.\,pop.\,density + Added\ NoVA\ area \cdot Added\ NoVA\ pop.\,density} = \frac{1}{1.440} \text{ (eq2)}$$

So, adding NoVA to the simulation would increase car counts by **~1.44x.**
Final hourly trip counts for total simulation network (D.C. + NoVA regions)**:**
(i) 25,131 x 1.44 = **~36,188** trips per hour *(representative of Off-hours)*
(ii) 82,962 x 1.44 = **~119,465** trips per hour *(representative of AM rush)*
(iii) 69,539 x 1.44 = **~100,136** trips per hour *(representative of Midday)*
(iv) 83,675 x 1.44 = ~**120,492** trips per hour *(representative of PM rush)*
In summary, to approximate the effects of eco-routing and congestion zone pricing across the D.C. area's changing daily traffic patterns, we simulate:
(i) the **Off-hour** time period to use **36,188** vehicles/hour
(ii) the **AM rush** time period to use **119,465** vehicles/hour
(iii) the **Midday** time period to use **100,136** vehicles/hour
(iv) the **PM rush** time period to use **120,492** vehicles/hour

2.5 Warm-up Period
Once the number of vehicles and the routes have been calculated, vehicles need to be fed into the road network. To do so realistically, all simulations are divided into two sections: a 1-hour warm-up period and a 1-hour observation period.
(i) **Warm-up period:** The use of a warm-up period is an industry standard for traffic simulations, which mitigates inaccuracies that may arise from taking measurements immediately after car generation [24]. If vehicle trips were generated all at once, they could overwhelm choke points in the network and form artificial "traffic explosions." Thus, each simulation begins with a 1-hour warm-up period to allow vehicle populations time to accumulate and arrange themselves into steady, naturally occurring flows before measurements are taken. A one-hour warm-up period is more than enough time because the Department of Transportation Traffic Analysis Toolbox [24] recommends warm-up periods be at least 2x the average trip time in free-flow conditions, which we recorded to be ~16 minutes for our simulations.
(ii) **Observation Period:** During the observation period of the simulation, SUMO sums CO_2 count and VMT (vehicle miles travelled) for all vehicles, saving the totals to a results file once the observation period is finished [11]. As mentioned before, CO_2 counts are calculated using the HBEFA4/PC_petrol_Euro-6d emissions class.
For all two hours of the simulation, cars are generated evenly at a rate of *n* per hour, where *n* is the number of trips expected to be generated in the D.C. area for that given hour of the day (*n*-values are taken from 2.4.3). Since routes are finished at approximately the same rate as they generate, car counts in the simulation stabilize after the first trips finish. This way, the number of cars at any given time is constant by the time the observation period begins, and the transition from warm-up to measurement period is seamless.

3. Results and Discussion

3.1 Simulation Structure

A total of 480 simulations were run across 4 time frames, 4 simulation types, and 3 zone access rates, isolating each factor for independent analysis. The simulations are divided according to the diagram below.

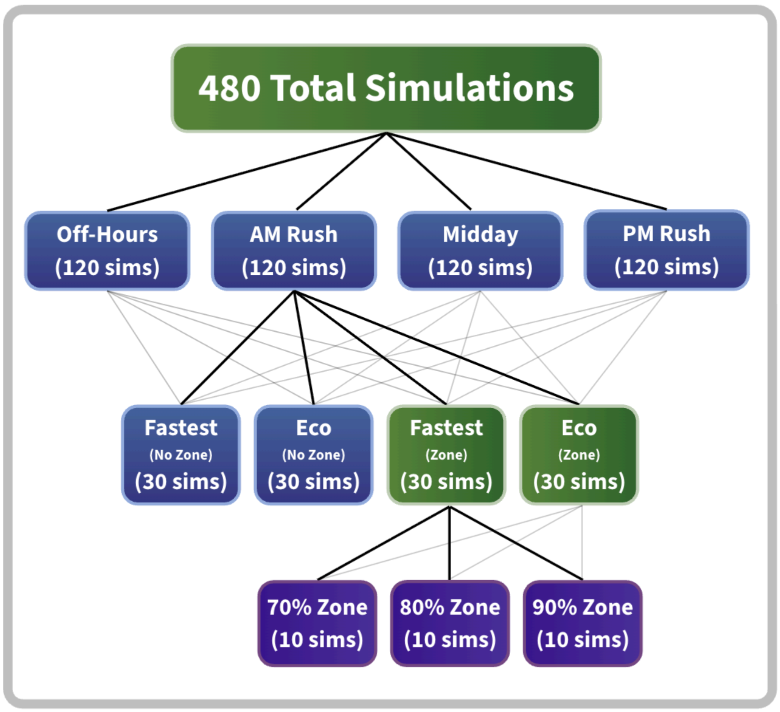

Figure 4. Hierarchical structure of the 480 simulations conducted in this study. Simulations were divided across four time frames (Off-Hours, AM Rush, Midday, PM Rush), four routing/zone cases (Fastest no-zone, Eco no-zone, Fastest with zone, Eco with zone), and three congestion zone access rates (70%, 80%, 90%), with 10 trials per unique parameter combination. Dividing simulations into four representative time frames allows effects to be modeled while taking into account the whole day of D.C.'s traffic patterns. As illustrated above, each time frame uses unique vehicle counts and driving patterns derived from real-world estimates during that time frame. Additionally, the setup of four sub-cases per time frame isolates how the eco-routing and congestion zone affect traffic independently, as well as how different routing affects traffic when used jointly with a congestion zone. Finally, zone access rates were varied in increments of 10% from 70%-90% to test a reasonable range of congestion zone access rates, and each unique set of simulation parameters was run in groups of 10 trials. This sums to 480 total simulations.

3.2 Analyzing Eco-routing (no zone) vs. Fastest-routing (no zone)

Using the 30 simulations of fastest and eco routes for the 4 distinct time periods, the means of CO_2 emitted were calculated.

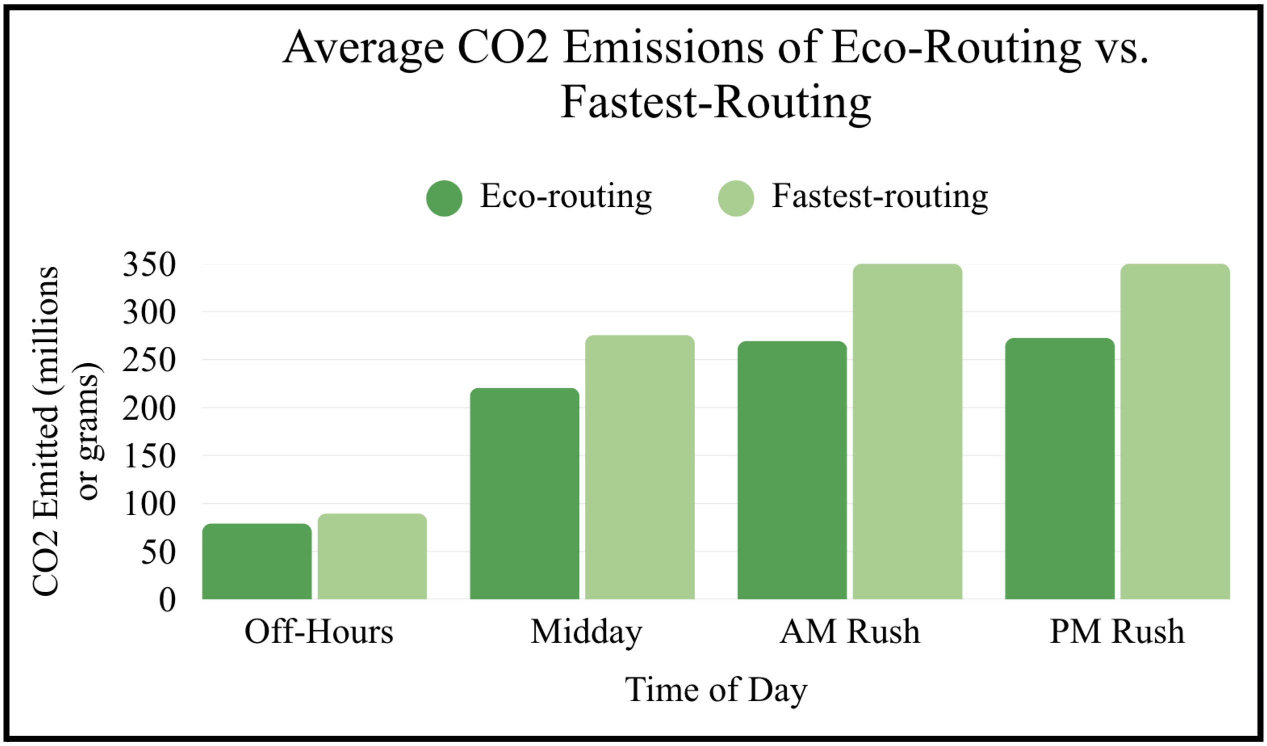

Figure 5. Average CO_2 emissions of eco-routing versus fastest-routing across the four time frames, with no congestion zone applied. Each bar represents the mean across 30 simulations.

Table 2. Average CO_2 emissions savings from eco-routing compared to fastest-routing across the four time frames, with no congestion zone applied.

	Mean CO_2 Saved (g)	**Mean % CO_2 Reduction**	**Mean % CO_2 Reduction 95% Confidence Interval**
Off-Hours (36k vehicles)	10,513,162	11.76%	± 0.03%
Midday (100k vehicles)	54,924,797	19.92%	± 0.46%
AM Rush (119k vehicles)	80,584,844	23.03%	± 0.34%
PM Rush (120k vehicles)	77,353,655	22.09%	± 0.69%

Over the span of each of the different car populations, eco-routing consistently showed a decrease in CO_2 emissions. The average CO_2 saved for a 36,188 car simulation, 100,136 car simulation, 119,465 car simulation, and 120,492 car simulation was approximately 10.5 million g CO_2, 54.9 million g CO_2, 80.6 million g CO_2, and 77.3 million g CO_2, respectively. Considering this simulation was only 1 hour in real-time, this amounts to substantial emission savings throughout the whole day. In total, eco-routing proved to save approximately 11-23% of carbon dioxide emissions compared to fastest routes, depending on the time of day, underscoring the significance that implementing eco-routing can have on reducing climate change. Thus, we conclude that eco-routing, if fully implemented in the D.C. area, would result in significant emission savings compared to the standard fastest-route GPS settings among commuters.

3.3 Analyzing Fastest-routing (no zone) vs. Fastest-routing (zone)

3.3.1 *CO_2 Emission Breakdown*

To investigate the CO_2 benefits of congestion zone, we calculated the total CO_2 penalty that the congestion zone brings (consisting of various access rates):

$$Total\ \%\ Change\ in\ CO_2 = \frac{CO_{2\ \ Case\ 3} - CO_{2\ \ Case\ 1}}{CO_{2\ \ Case\ 1}} * 100 \text{ (eq3)}$$

$CO_{2\ (Case\ 1)}$ represents the average carbon dioxide emissions from the fastest (no zone) routes, and

$CO_{2\ (Case\ 3)}$ represents the average carbon dioxide emissions from the fastest (zone) routes.

Then, in order to pinpoint the cause of the aforementioned CO_2 penalty, we break down the CO_2 calculation into two factors: VMT (vehicle miles travelled) and Efficiency (avg. miles per gram of CO_2).

$$Total\ CO_2\ Emitted\ = \frac{VMT}{Efficiency} \text{ (eq4)}$$

3.3.2 *CO_2 Penalty Due to Extra Distance*

When a congestion zone is established, many cars are rejected and travel an alternative, often longer, route to reach their destination. This extra distance likely hindered the effectiveness of our congestion zone (despite the fact that the congestion zone brought fewer CO_2 emissions within the congestion zone region). In order to quantify the effects of extra distance on the CO_2 penalty, we utilize Vehicle Miles Traveled (VMT) data, outputted by SUMO. It is important to note that while routes were initially set to be approximately 7-8 miles (see section 2.4 of the Procedure), rerouting and rejection from the congestion zone would bypass that rule. This is because the true distance, in reality, would be 7-8 miles using the congestion zone, but avoiding the congestion zone would force vehicles to reroute and travel a longer distance to their destination. Using VMT data, we perform the following calculation to obtain the CO_2 penalty due to the extra distance the vehicles must travel:

$$\%\ Change\ in\ CO_2\ Due\ to\ Distance\ = \frac{VMT_{\ Case\ 3} - VMT_{\ Case\ 1}}{VMT_{\ Case\ 1}} * \ 100 \text{ (eq5)}$$

This tells us the percent increase in distance that the vehicles travel in the simulation.

3.3.3 *CO_2 Penalty Due to Efficiency Loss*

The other factor affecting carbon emissions is efficiency. In other words, it is the amount of CO_2 emitted for every mile that a vehicle travels. This reveals how various factors, such as idling and "stop and go traffic," may impact emission numbers. By tracking efficiency, along with extra distance traveled, we can prove whether the congestion zone failed because of an increase in congestion or simply because of greater distance traveled. This factor is likely what will cause our congestion zone to ultimately work. After all, the purpose of a congestion zone is to decrease congestion and therefore CO_2 emissions in a city by mitigating the inefficiencies of the "stop and go traffic." To obtain the efficiency, we used the formula:

$$Efficiency = \frac{Total\ VMT}{Total\ CO_2} \quad \text{(eq6)}$$

Then, we measured the efficiency loss to equal:

$$\%\ Change\ in\ CO_2\ Due\ to\ Efficiency = \frac{Efficiency_{Case\ 3} - Efficiency_{Case\ 1}}{Efficiency_{Case\ 1}} * 100 \quad \text{(eq7)}$$

This measures the percent loss of efficiency in the congestion zone simulation compared to the standard simulation.

3.3.4 *Discussion of Congestion Zone Impacts*

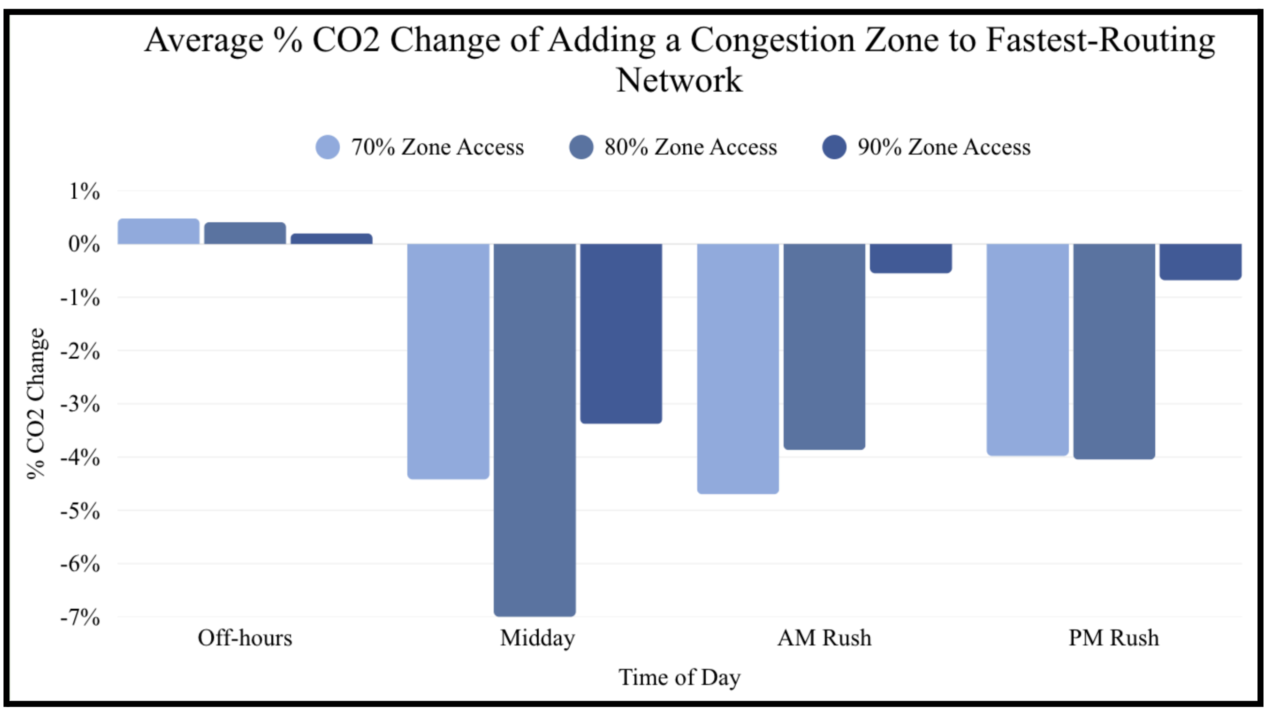

Figure 6. Average percent change in CO_2 emissions from adding a congestion zone to a fastest-routing network, shown across the four time frames and three zone access rates (70%, 80%, 90%). Negative values indicate emission reductions; positive values indicate emission increases.

Table 3. Breakdown of total CO_2 percent change, percent change due to distance, and percent change due to efficiency loss, for fastest-routing with a congestion zone compared to fastest-routing without a zone. Results are shown across four time frames and three zone access rates.

Scenario	Zone Access	Total CO_2 % Change	Total CO_2 % Change 95% Confidence Interval	CO_2 % change due to distance	CO_2 % change due to efficiency
36k (Off-hours)	70%	0.48%	± 0.06%	0.22%	0.26%
	80%	0.41%	± 0.07%	0.15%	0.26%
	90%	0.20%	± 0.05%	0.07%	0.13%
100k (Midday)	70%	-4.42%	± 2.19%	0.74%	-5.16%
	80%	-7.43%	± 1.65%	0.75%	-8.18%
	90%	-3.38%	± 4.65%	0.10%	-3.48%
119k (AM Rush)	70%	-4.70%	± 0.79%	3.04%	-7.74%
	80%	-3.87%	± 0.94%	2.09%	-5.96%
	90%	-0.55%	± 0.84%	0.99%	-1.54%
120k (PM Rush)	70%	-3.98%	± 1.83%	2.87%	-6.84%
	80%	-4.05%	± 1.31%	1.92%	-5.97%
	90%	-0.68%	± 0.98%	1.00%	-1.68%

When added to a network using fastest routing, the congestion zone consistently demonstrated a total negative percent change (a reduction) in CO_2 emissions throughout the Midday, AM Rush, and PM Rush simulations. However, the congestion zone was ineffective during Off-hours, marked by a positive percent change of 0.20% to 0.48%. This is due to the fact that congestion zones are less effective during times when there is minimal traffic; they are designed for high-traffic environments. For all scenarios except for Off-hours, although the congestion zone caused vehicles to travel longer distances, the overall efficiency gains from avoiding stop-and-go traffic resulted in a net negative CO_2 change. According to our model, the optimal zone access rate for the congestion zone varied across times of day. For Midday and PM Rush, the lowest simulated CO_2 emissions occurred at zone access rate was 80%, and for AM Rush, 70% was best. Again, the congestion zone did not cause CO_2 improvements during Off-hours. In practice, these results highlight the necessity for a dynamic time-based congestion zone: our model indicates that an effective congestion zone policy would be inactive during Off-hours, with a higher fee during the morning, and a lower fee during Midday and PM Rush. Overall, the congestion zone demonstrates potential to considerably reduce CO_2 emissions, as the zone reached up to 7.43% CO_2 savings at its peak.

3.4 Analyzing Eco-routing (zone) vs. Eco-routing (no zone)

All of the calculations and factors included in Part IIa are used here as well. However, instead of using Case 3 (fastest routing + congestion zone) vs Case 1 (fastest routing alone), we use Case 4 (eco-routing + congestion zone) vs. Case 2 (eco-routing alone). This allows us to analyze the effect of an added congestion zone while eco-routing is present in the network.

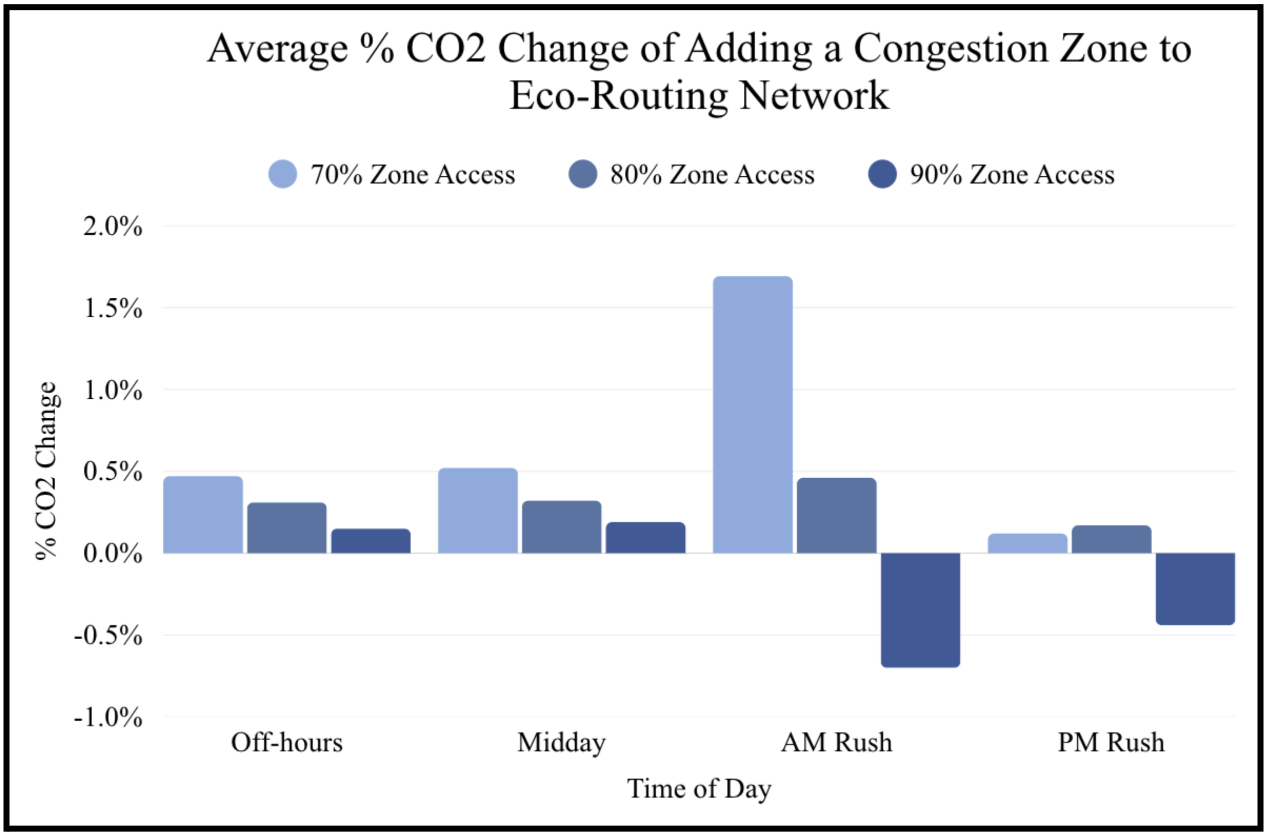

Figure 7. Average percent change in CO_2 emissions from adding a congestion zone to an eco-routing network, shown across the four time frames and three zone access rates (70%, 80%, 90%). Negative values indicate emission reductions; positive values indicate emission increases.

Table 4. Breakdown of total CO_2 percent change, percent change due to distance, and percent change due to efficiency loss, for eco-routing with a congestion zone compared to eco-routing without a zone. Results are shown across four time frames and three zone access rates.

Scenario	Zone Access	Total CO_2 % Change	Total CO_2 % Change 95% Confidence Interval	CO_2 % Change Due to Distance	CO_2 Change Due to Efficiency
36k (Off-Hours)	70%	0.47%	± 0.04%	0.45%	0.02%
	80%	0.31%	± 0.02%	0.30%	0.01%
	90%	0.15%	± 0.02%	0.14%	0.01%
100k (Midday)	70%	0.52%	± 0.03%	0.46%	0.06%
	80%	0.32%	± 0.06%	0.30%	0.02%
	90%	0.19%	± 0.03%	0.16%	0.03%
119k (AM Rush)	70%	1.69%	± 0.92%	3.34%	-1.65%
	80%	0.46%	± 0.62%	1.50%	-1.04%
	90%	-0.70%	± 0.49%	1.19%	-1.89%
120k (PM Rush)	70%	0.12%	± 0.35%	3.27%	-3.15%
	80%	0.17%	± 0.34%	2.18%	-2.01%
	90%	-0.44%	± 0.88%	1.09%	-1.53%

The combination of both eco-routing and the congestion zone mostly did not reveal an improvement in CO_2 emissions. In almost all cases, with the exception of the 100k and 120k simulations at a 90% access rate, the CO_2 percent change was positive, indicating that the congestion zone actually increased CO_2 emissions. This may be caused by the fact that eco-routing and congestion zones have very similar functions: to divert cars onto smaller, less traffic-heavy roads at the expense of increased distance. When both techniques are used together, we hypothesize that their effects interfere, flooding the smaller routes with new bottlenecks that would be less optimal than the original routes, thus resulting in higher overall CO_2 emissions. In the table, this conclusion is supported by the fact that increases in travel distance consistently outweighed efficiency gains from the altered route. Therefore, under our modeled design, eco-routing and congestion zones did not provide meaningful CO_2 reduction in the Washington D.C. area, suggesting possible redundancy or interference between the two methods.

3.5 Analyzing Time Expenditure

While an eco-route can meaningfully reduce vehicular carbon emissions, it is important to consider how much time is lost in implementing eco-routes instead of the fastest routes on a full scale. Thus, we investigate the following data for the trip duration we received from our simulations. As a point of validation, our rush-hour trip times reasonably match average commute times within D.C. as measured by the D.C. Policy Center [25].

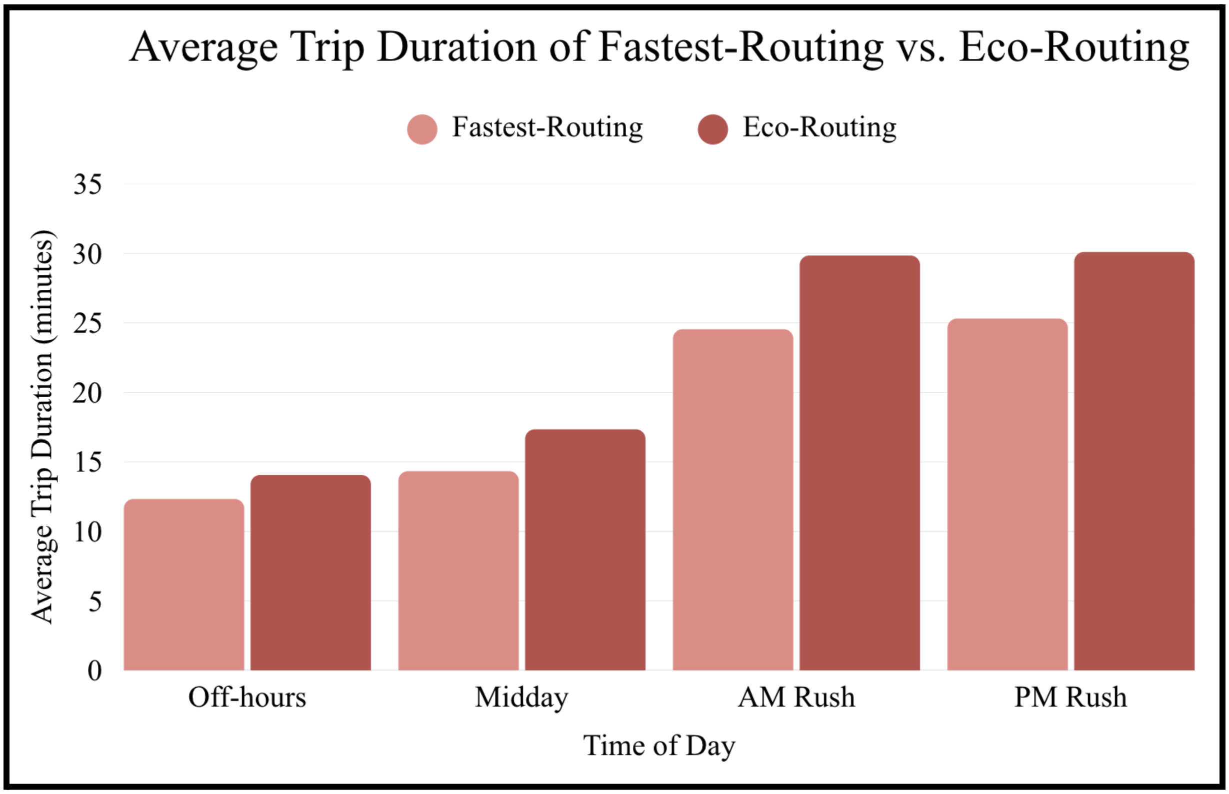

Figure 8. Average trip duration of fastest-routing versus eco-routing across the four time frames, with no congestion zone applied. Each bar represents the mean trip duration across 30 simulations.

Table 5. Comparison of mean trip duration between fastest-routing and eco-routing across the four time frames, with no congestion zone applied. Mean times are reported in minutes; absolute and percent time loss from eco-routing are reported relative to fastest-routing.

Scenario	Fastest-routing Mean Time (min)	Eco-routing Mean Time (min)	Time Lost from Implementing Eco-routing (min)	% Time Lost from Implementing Eco-routing	% Time Lost from Implementing Eco-routing 95% Confidence Interval
36k (Off-Hours)	12.33	14.06	1.73	12.32%	± 0.04%
100k (Midday)	14.33	17.34	3.02	17.29%	± 1.07%
119k (AM Rush)	24.54	29.84	5.30	17.51%	± 1.74%
120k (PM Rush)	25.31	30.09	4.78	15.84%	± 1.16%

During off-hours, eco-routes resulted in a time loss of approximately 12%, or a roughly ~2-minute increase per 12-minute trip. However, during periods of higher demand, time losses due to eco-routing jump to approximately 16-18% or a time loss of up to ~5 minutes. This would be the trade-off for an eco-routing algorithm that produces an 11% to 23% reduction in CO_2. In other words, sacrificing a small delay for drivers in D.C. can accumulate substantial CO_2 savings overall.

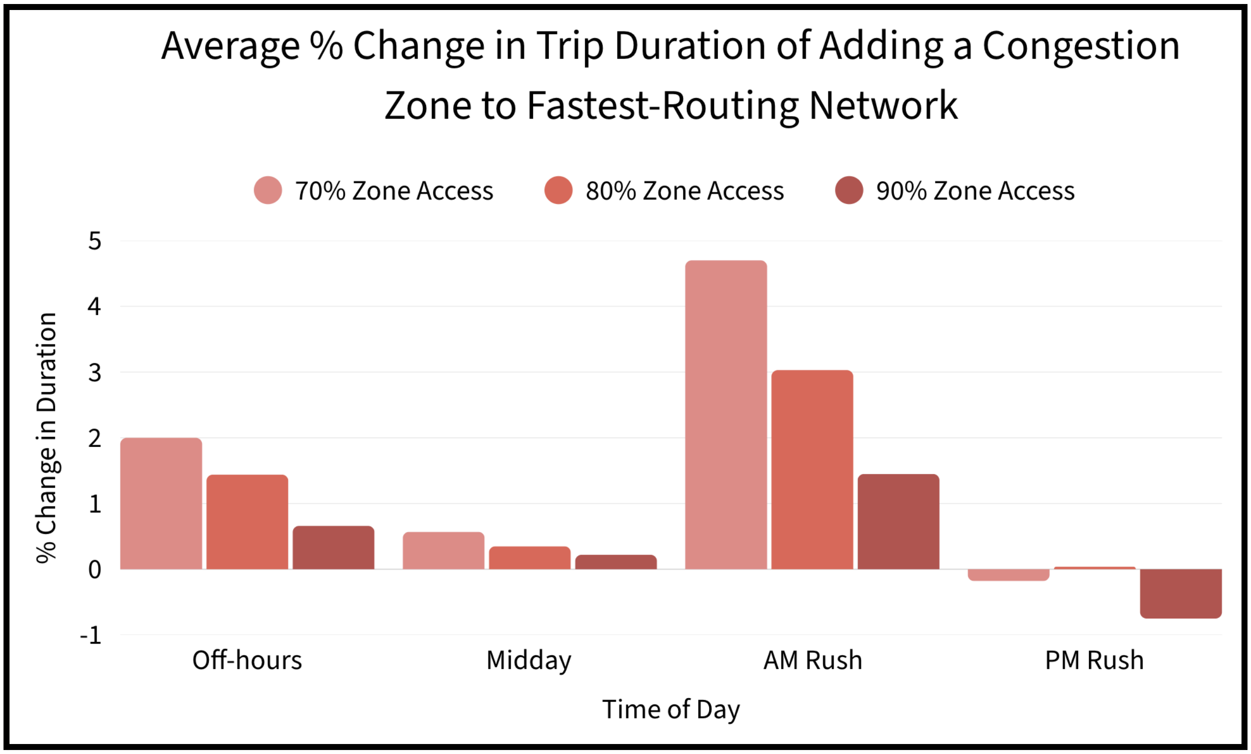

Figure 9. Average percent change in trip duration from adding a congestion zone to a fastest-routing network, shown across the four time frames and three zone access rates (70%, 80%, 90%). Positive values indicate longer average trips; negative values indicate shorter average trips.

Table 6. Comparison of mean trip duration between fastest-routing without a congestion zone and fastest-routing with a congestion zone, shown across four time frames and three zone access rates. Time saved is reported in minutes (negative values indicate increased trip duration); percent change is reported relative to fastest-routing without a zone.

Scenario	Zone Access %	Fastest Routing (min)	Trip Duration w/ Zone (min)	Trip Duration Reduction from Zone (min)	% Change in Trip Duration	% Change in Trip Duration 95%
36k (Off-Hour	70	12.33	12.58	-0.25	-2.04	± 0.12%

s)	80	12.33	12.51	-0.18	-1.44	± 0.14%
	90	12.33	12.41	-0.08	-0.66	± 0.07%
100k (Midday)	70	14.33	14.41	-0.08	-0.57	± 0.05%
	80	14.34	14.39	-0.05	-0.35	± 0.09%
	90	14.31	14.34	-0.03	-0.22	± 0.06%
119k (AM Rush)	70	24.57	25.73	-1.16	-4.70	± 1.10%
	80	24.50	25.24	-0.74	-3.03	± 0.69%
	90	24.55	24.90	-0.36	-1.45	± 0.62%
120k (PM Rush)	70	25.26	25.21	0.05	0.18	± 0.42%
	80	25.17	25.18	-0.01	-0.04	± 0.52%
	90	25.48	25.29	0.20	0.75	± 1.02%

Barring the PM Rush period, the addition of a congestion zone consistently produced slight increases in average trip durations, by up to ~2% in the Off-hours simulations and up to ~5% for the AM Rush simulations. This is mostly due to vehicles being rerouted by the zone onto slower but more carbon-efficient routes. Scenarios with lower access rate congestion zones tended to incur larger time losses than those with higher access percentages, likely because lower access rates would mean more cars getting diverted from the center. Notably, there is a sharp contrast between duration changes in the AM Rush and PM Rush periods. The AM Rush experienced the largest time delays due to the congestion zone, likely because the flow of traffic moving towards the CBD caused numerous cars to get redirected from it. The PM Rush period did not follow this pattern, however, maintaining a roughly neutral change in time, likely due to the overall trend of cars traveling outward from the center.

4. Conclusion

Eco-routing, if fully implemented in the D.C. area, can produce substantial CO_2 emission savings of ~11-23% compared to fastest-routing algorithms, with trips taking ~12-18% longer on average. Alternatively, the introduction of a dynamic congestion zone policy in the D.C. area alongside fastest-routing could reduce CO_2 emissions by 7.4%, with minimal increases in trip duration. From our data, this policy would optimally adopt an 80% access rate during Midday and PM Rush, a 70% rate for AM Rush, and have no fee at all during off-hours, though future research could optimize the fees and timing more precisely. When eco-routing and congestion zones are implemented together, this scenario actually slightly raises carbon emissions compared with just eco-routing alone; they are optimal in isolation. This is likely because both features are designed to divert cars onto smaller roads, and their effects interfere, overwhelming the smaller roads when combined. Thus, this research lays the groundwork for the potential implementation of new governmental traffic policies and provides evidence that traffic policy interventions can achieve considerable reductions in vehicular CO_2 emissions within urban networks, at the expense of slightly longer travel times. Moreover, the benefits of greater vehicle efficiency from eco-routing and congestion zones can additionally extend towards fields such as energy sustainability, urban air quality, and extreme weather reduction.

5. Limitations/Future Work:

We do note that there are several limitations with our simulation, which may introduce a level of uncertainty to the results of our study. First, many of the statistics used in designing the simulation are approximate by nature. For example, the distribution of route lengths was modeled using national average estimates, the total counts of generated trips were approximated using historical hourly averages, and the spatial distributions of routes were roughly estimated using transportation statistics. Further, the geography of the road network and traffic-analysis divisions was defined approximately for the sake of simplicity. Future work could be based on more rigorously attained information to maintain a higher degree of accuracy. Second, all cars were simulated to use the same type of engine and adopt the same driver behavior. In reality, a diverse mix of vehicles drive through D.C. with varying engine efficiencies, including a small number of electric vehicles. For this study, all vehicle emissions were calculated using the HBEFA-Euro-6d emission class as an approximate estimate for vehicle engines. Additionally, vehicles in this simulation also followed traffic rules strictly; in the real world, some cars may drive slower or faster than the speed limit, and occasionally violate traffic rules. Future studies could incorporate this detail by accounting for appropriate vehicle diversity and variation in driver behavior. Third, we approximated the functionality of our congestion policy zone. Rather than setting a precise congestion fee and simulating whether drivers would pay (which is extremely complex to model), a constant zone access rate was applied to the Central Business District to strictly limit a certain proportion of vehicles from entering. This model is very similar in final outcome to simulating a monetary fee. Future work could build upon this by finding the correlation between zone access percentages and monetary tolls in the Washington, D.C. area, increasing the applicability of results, and enabling estimation of expected government revenue from this policy. Fourth, we assume that overall vehicle demand stays constant with the implementation of a congestion zone fee. In the real world, congestion zone pricing has a side-effect of encouraging travellers to switch their mode of transport from cars to public transit or walking/biking, rather than only adjusting their routing behavior as we model. Similarly to congestion fees, this detail about demand change was omitted, because human decision-making is extremely complex and would likely be inaccurate to simulate. If anything, though, this omission of detail would cause our results to underestimate the potential benefits of a congestion zone rather than overestimate them. Future research could attempt to model humans switching modes of transport in response to a congestion zone fee. Accordingly, considering these limitations, our results should be treated as simulated averages rather than definitive statistics. However, it is important to note that relative trends in CO_2 emissions and traffic patterns likely remain meaningfully accurate despite limitations with simulation design; our study is intended to be comparative and not predictive.

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