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A ROAD TRAFFIC QUEUEING MODEL BALANCING EMISSIONS AND COST

by
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ABSTRACT
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This paper examines a highway system using a queueing theory model, with parameters estimated from realistic data. Preliminary results include estimation of key performance indicators such as throughput, mean number of vehicles, and emissions. The model identifies the optimal number of lanes and speed limit that minimizes the combined costs of road construction and traffic delays. Additionally, the study extends to include a second objective, which is minimizing carbon emissions. Our results, comparing the results of both objectives, demonstrate that emissions considerations can influence the design of highway systems, and lead to significantly higher costs. In order to explore the trade-offs between reducing costs and emissions, we analyze this resulting two-objective optimization through the characterization of Pareto-optimal (efficient) solutions and their application to realistic scenarios. We observe that significant cost saving can be achieved (e.g. 20%) if one allows a small increase in emissions (e.g. by 0.5%) over the level stipulated by the single-objective emission minimization model.

Keywords: Traffic, queueing theory, carbon emissions, highway planning.

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ABBREVIATIONS

Symbol	Unit	Description
c	-	Capacity of the system
j	-	Number of vehicles on the road segment
k	-	Jam Capacity
l	*(km)*	Length of the segment
n	-	Number of Lanes
v_j	*(km/hr)*	Speed as a function of the number of vehicles
v_1	*(km/hr)*	Free flow speed
μ_j	*(veh/hr)*	Service Rate
λ	*(veh/hr)*	Arrival rate (car/hr)
α	-	Service level measure
C_s	*($/lane/hr)*	Cost of providing service per hour
C_w	*($/veh/hr)*	Cost of providing service per hour
C_t	*($/kg CO_2)*	Carbon Tax
EC	*($/hr)*	Expected Cost
EC^e	*($/hr)*	Expected cost rate with environmental considerations
EE	*(kg/hr)*	Total emissions rate
E_c	*(kg/hr/lane)*	Emissions rate of building one lane
$H(v_j)$	*(kg/km)*	CO_2 emissions produced per kilometer by a vehicle traveling at v_j
I	*(kg/hr/veh)*	Hourly rate of CO_2 emissions per vehicle

L	-	Expected number of vehicles in the system
A, B, C, m	-	Positive constants
RoCO	-	Road Cost Optimization Model
RoCO-EC	-	Road Cost Optimization Model with Emisisons Cost
RoEO	-	Road emission optimization Model
RECO	-	Road Environmental impact and Cost Optimization Model
RECO-P	-	Road Environmental impact and Cost Optimization Model with Pareto Behavior
P_0	-	Probability of finding the system empty
P_j	-	Probability of having j vehicles in the system
P_c	-	Probability of finding full system

CHAPTER 1

INTRODUCTION AND MOTIVATION

Global warming presents a critical global threat due to the rise of greenhouse gas emissions. In response, countries worldwide are implementing legislation and regulations to alleviate and mitigate its impact (Nema et al., 2012). Many organizations are prioritizing environmentally friendly technologies, such as improving the sustainability of raw materials, enhancing waste management practices, and investing in green processing. However, implementing these technologies can be costly and time-consuming. In addition to these technological improvements, businesses can also reduce emissions through operational strategies. This work highlights the effectiveness of cost-friendly operational strategies for reducing carbon emissions, specifically through designing and managing queueing systems in the transportation sector, where emissions are closely linked to congestion.

To effectively address emissions and operational costs in the transportation sector, it is essential to utilize modeling techniques that capture the dynamics of traffic congestion, resource utilization, and vehicle speed (including speed limits). Queueing theory offers a mathematical framework to address these dynamics, with applications spanning various industries, including manufacturing, logistics, transportation, communication, computer networks, among others. It plays an essential role in establishing optimal resource levels, servers, and service disciplines to meet service requirements while minimizing costs. Queueing theory provides a mathematical framework to quantify both waiting time (congestion) and service supply expenses/requirements (Shortle et al., 2018).

Despite its broad applicability, our literature review reveals that research on queueing systems often overlooks the impact of congestion on emissions, even though they are naturally correlated across various applications. In the transportation sector, emissions increase as vehicles spend more time idling in traffic on highway systems (Smit et al., 2008). This also extends beyond highways with applications in maritime transportation where ships queue for berth at ports, such as the Suez Canal (Cullinane & Cullinane, 2013). Similarly, in aviation, airplanes waiting on taxiways at airports also contribute to increased emissions. Other applications of queueing theory that exhibit emission caused by congestion include internet networks. For instance, Google's data centers produce approximately 2.9 tons of CO_2 emissions, representing 24% of their carbon footprint, mainly due to the electricity demands of their servers (Google Sustainability, 2022). Similarly, power generation for generative AI servers running large language models (LLMs) result in substantial greenhouse gas emissions (Berthelot et al., 2024).

This work presents a queueing model that captures the dependency between congestion and emissions in traffic, as a first step towards further application of queueing theory in the design of sustainable systems. Queueing theory typically analyzes two types of traffic systems: interrupted flows, which are affected by intersections, signs and signals and uninterrupted flows, as typically encountered on freeways and highways (Elefteriadou, 2014). This work considers the continuous flow approach to represent road segments frequently accessed by residential areas.

The models developed in this work examine the dependencies between traffic congestion, travel speed (including speed limits) and emissions. For example, as congestion increases, traffic speed decreases, resulting in higher carbon emissions. While

increasing speed limits can reduce congestion, higher speeds on lightly congested road segments can also lead to higher emissions, as vehicles traveling at high speeds produce more emissions. The relationship between speed and emissions is not monotone (Alessandrini et al., 2012, Sbayti et al., 2002), therefore, minimizing both cost and emissions is achieved at moderate travel speeds within an efficiently designed traffic system.

The rest of this report is structured as follows: Chapter 2 presents a literature review of related works. Chapter 3 provides the proposed models and assumptions. Chapter 4 presents the numerical analysis, covering parameter estimation, sensitivity analysis, and optimization strategies for both speed limits and number of lanes. Finally, Chapter 5 concludes the report by summarizing key findings and highlighting future research directions.

CHAPTER 2

LITERATURE REVIEW AND BACKGROUND

This chapter briefly reviews the related literature. Section 2.1 provides a brief review and background on attempts to study emissions in operations management models, while Section 2.2 examines works that apply queueing theory in a road traffic context. Finally, Section 2.3 discusses empirical evidence on the association between vehicle speed and carbon emissions.

2.1. Modeling Emissions in Operations Management

Integrating environmental sustainability into operations management has become increasingly critical. The main focus of emission modeling is to quantify and mitigate the environmental impact of the operational activities (Sundarakani et al., 2010). While significant advancements have been made in areas such as transportation planning, supply chain management, and inventory control (Bazan et al., 2015) studies that integrate emissions into queueing models remains limited (Leogrande, 2024).

Emissions modeling is instrumental in optimizing carbon emissions across different stages of the supply chain, from sourcing raw materials to final distribution. Green supply chain management frameworks rely on carbon footprint assessments to quantify emissions associated with storage, production, and distribution (Aziziankohan et al., 2017). These assessments are key for sustainable decision making, such as optimizing transportation routes, suppliers selection and waste minimization (Carter & Rogers, 2008). To provide a comprehensive view of both financial and environmental performance, advanced models also integrate emissions costs (Liu et al., 2024).

Moreover, studies have also explored the effect of coordination mechanisms between retailers and manufacturers. For example, Jaber et al (2017) studies a two-level closed-loop supply chain model, focusing on reducing carbon emissions by remanufacturing and energy use.

In inventory management, emissions modeling has been particularly valuable for optimizing inventory levels while including emissions linked to warehousing, transportation, and product returns. Excess inventory can lead to higher emissions due to increased storage requirements, additional handling, and waste from unsold goods. To balance inventory costs with environmental impact, studies model emissions across the entire lifecycle, from transportation and storage to disposal (Becerra et al., 2022). Sakaya (2015) builds on this work on this work by simulating two-product joint replenishment systems, indicating how coordinated replenishment approaches can reduce emissions by improving transportation and storage operations.

Companies with high turnover rates tend to reduce both emissions and costs by optimizing reorder points, order quantities, and product returns. Frequent replenishments increase the risk of emissions due to excessive transportation and storage (Palevich, 2011). Reducing emissions not only offers a competitive advantage to companies across various industries, but it also fulfils regulatory requirements. Many sectors now operate under emissions caps, trade schemes, and sustainability reporting mandates (Tang & Zhou, 2012).

Emissions modeling has evolved significantly with advancements in data analytics and machine learning by providing models that closely examine and capture greenhouse emissions patterns and behaviors. With these advancements, real-time emissions data from IoT sensors have enhanced monitoring and predicting capabilities,

allowing operations to adapt dynamically to current emissions levels (Rauniyar et al., 2022). Additionally, artificial intelligence (AI) tools are helping to minimize emissions in ways that traditional models are unable to achieve (Arya et al., 2024).

2.2. Queuing Theory in Road Traffic

Queueing theory plays a major role in understanding and modeling traffic flow dynamics. Contributions to this filed include Jain & Smith (1997) who analyze who model congestion in continuous flow systems. They model a road segment as an Erlang loss system, $M/G/c/c$, with state-dependent service rates. These rates reflect the decrease in travel speed, as congestion on the road increases, down from the "free-flow" speed when only one car is on the road segment, which is assumed to be the highway speed limit. Many papers adopt a model similar to Jain & Smith (1997) including Raj & Khode (2016) and Van Woensel & Vandaele (2007). In this paper, we adopt the Jain & Smith (1997) traffic model and augment it with a queueing cost and emission models and use those to propose alternative road designs in terms of number of lanes and speed limit. As such our work contributes (i) a cost model reflecting congestion levels that can be used for high-level road design, (ii) a framework that allows estimating emission born from congestion, and (iii) simple optimization models that allow us to explore the trade-off between cost and emission in road design.

Another application of queueing theory in traffic management involves studying the behavior of queues at signalized intersections. Conventional models, such as M/M/1 and M/G/1 queues, are used (Viloria et al., 2000, Brilon, 2008, Gautam, 2012). Advances in real-time data availability and computational power have further enabled adaptive

signal control systems, which can now dynamically model the signal phases based on current traffic conditions (Maadi et al., 2022).

Queueing theory also provides valuable insights into traffic management. Rapid queueing and congestion often result from incidents that temporarily reduce roadway capacities. Queueing theory can be applied to predict the length and duration of these queues, to estimate the impact of congestion on roadways (Newell, 2013). Such models are particularly useful for setting incident response strategies that accelerate recovery times and minimize disruption (Papageorgiou, 2004).

In public transportation systems, queueing theory is used to reduce waiting times at transit stops and stations. Researchers treat each stop as a queueing node to analyze waiting times based on the arrival and service rates of trains and buses (Daganzo, 1997). Queueing theory has also played a major role in the evolution of intelligent transportation systems (ITS) and connected vehicle technology. Through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, queueing models can coordinate autonomous vehicles at intersections and optimize overall traffic flow (Talebpour & Mahmassani, 2016).

2.3 Emissions as a function of vehicle speed

Vehicle emissions contribute to pollution through the release of gases such as CO, CO2, HC, and NOx from their exhaust systems. The proportion of the pollutants emitted varies based on factors such as vehicle type, fuel type, road and driving conditions, among other factors (Bokare & Maurya, 2013). While carbon monoxide gas, CO, has a lower direct greenhouse effect, its reactions can produce Methane and Ozone gases, which can significantly increase its greenhouse effect (Bokare & Maurya, 2013). Our work focuses

on CO2 emissions, as it constitutes the largest share of vehicle emissions and has the greatest greenhouse impact. However, the model can be extended to consider other pollutants that exhibit similar emission behavior patterns such as NOx, CO and HC (Achour et al., 2011, Sbayti et al., 2002) as illustrated in Figure 1.

Empirical studies in the literature indicate that CO_2 emissions follow a unimodal behavior as a function of car speed, where emissions per kilometer tend to be large at low speeds, decrease at around 70 km/h, and then rise again at higher speeds, as illustrated in Figure 1 adopted from Ntziachristos & Samaras (2000) who consider various driving cycles and emissions at different speeds in field and laboratory trials. As a result, they plotted the variation of emissions levels for several pollutants as a function of vehicle speed.

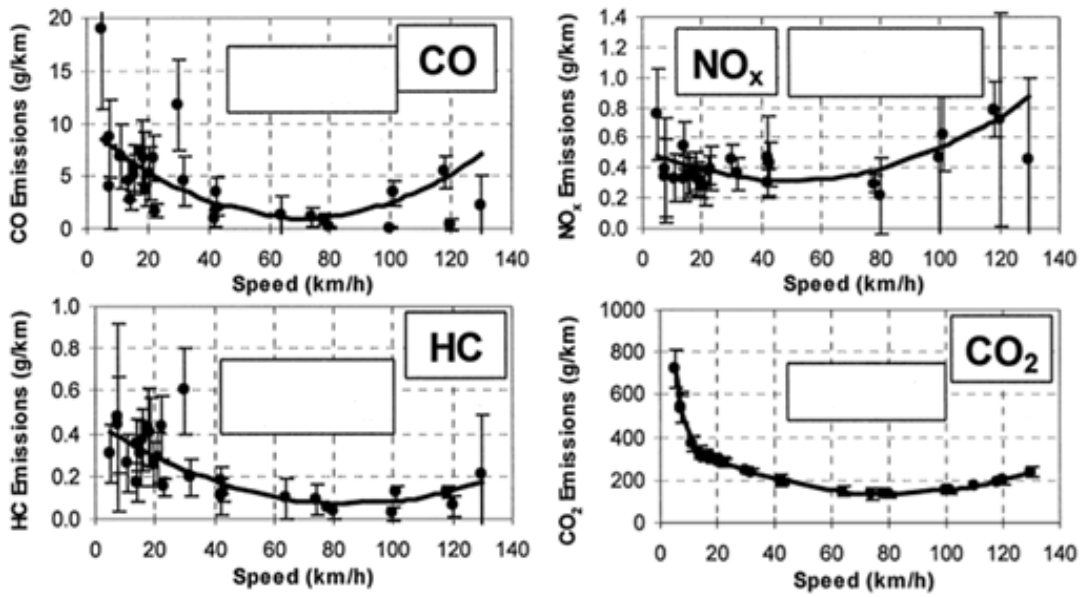

Figure 1. Emissions vs Car Speed (Ntziachristos & Samaras, 2000)

Despite the general observation of a unimodal relationship between CO_2 emissions and vehicle speed, the literature does not provide an analytical formula that

directly relates emissions to speed. In Section 4.1, we propose a function using a least-square curve fitting approach based on data from (Ntziachristos & Samaras, 2000).

CHAPTER 3

MODEL AND ASSUMPTIONS

This section presents our models and assumptions. Section 3.1 presents the base Erlang loss system relating speed and congestion, which we adapt mainly from Jain & Smith (1997). Section 3.2 utilizes the results of Section 3.1, to develop a road optimization model with an objective of minimizing expected cost. Section 3.3 presents a similar model with an objective of minimizing emissions. Finally, Section 3.4 discusses how the two objectives in Sections 3.2 and 3.3 can be integrated.

3.1 Erlang Loss Model Linking Speed and Congestions

We introduce the queueing traffic model adapted from Jain & Smith (1997) which is a *M/G/c/c* state-dependent queueing system. Consider a road segment of length *l (km)* with *n* lanes, where vehicles arrive at a rate of λ per hour according to a Poisson process. An arriving vehicle travels across the road segment at an average speed v_j *(km/hr)* where *j* represents the total number of vehicles on the segment. Let *k* be the "jam density," defined as the maximum number of vehicles that can be accommodated in one lane per kilometer. Thus, the capacity of the segment is

$$c = k \times n \times l. \quad (1)$$

Note that our usage of the term capacity differs from its typical use in transportation engineering, where it indicates the expected departure rate. We rather use the standard queueing theory conventions, where capacity denotes the number of slots (servers) that can accommodate vehicles (Shortle et al., 2018). Figure 2 illustrates the model.

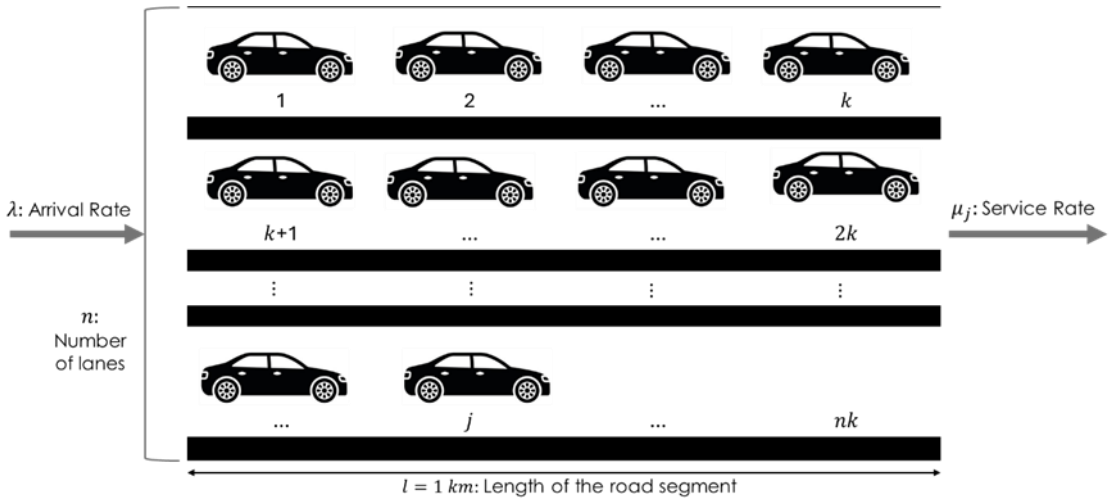

Figure 2. Block Diagram of the M/G/c/c Model of the Road Segment

The assumption of a Poisson arrival process is commonly adapted in traffic flow modeling (Qin & Smith, 2001, Islam, 2019). This is the case since the arrival process in traffic is typically the superposition of numerous processes. Moreover, the model assumes that vehicle dimensions are those of a typical passenger cars. For other vehicle types like trucks and buses, conversion factors can be used (HCM, 2022).

The car travelling speed is assumed to decreases linearly in the number of vehicles on the road segment, j, starting with the free-flow speed or speed limit v_1, when only one car is travelling along the road segment. The free-flow speed, v_1, is assumed to be equal to the speed limit on the road segment. When the road segment is at full capacity, the model assumes that the speed goes to 0, which is represented by $v_{c+1} = 0$. The speed as a function of the number of vehicles, j, on the road segment is represented as follows,

$$v_j = \left(\frac{v_1}{c}\right)(c+1-j),\ j = 1,2,\ldots,c. \tag{2}$$

Denote the "service" time to cross a road segment of length l with j vehicles by S_j, for $j = 1,2,\ldots,c$. the mean service time is $E[S_j] = l / v_j$. For simplicity, we assume, without loss of generality, that we have a road segment of length $l = 1$ km in the remainder

of the paper. This leads to a state-dependent service rate, which are identical to the speed in (2). Specifically,

$$\mu_j = \frac{1}{E[S_j]} = v_j. \tag{3}$$

The insensitivity of the Erlang system to service variability (Shortle et al., 2018) allows using the *M/M/c/c* birth-death equations to estimate the system size probability, i.e., the probability of having j vehicles on the road segment, P_j, $j = 0,\ldots,c$. Accordingly, based on standard birth-death processes analysis (Shortle et al., 2018), the system size probabilities are given by

$$P_0 = \left[1 + \sum_{i=1}^{c} \prod_{j=1}^{i} \frac{\lambda}{\mu_j}\right]^{-1}, \tag{4}$$

$$P_j = \left[\left(\frac{\lambda}{v_1}\right)^j \prod_{m=1}^{j} \frac{c+1-m}{c}\right] P_0,\ j = 1,2,\ldots,c. \tag{5}$$

An important performance measure that we use in the sequel is the expected number of vehicles on the road,

$$L = \sum_{j=1}^{c} jP_j. \tag{6}$$

3.2 Road Cost Optimization (RoCO) Model

For this model, we introduce the following additional parameters, the cost of providing service per hour, C_S ($/lane/hr), and the unit waiting cost, C_w ($/veh/hr). We adopt the standard queueing cost model (Shortle et al., 2018) combining the cost of providing service on a road of n lanes, which refers to the cost of building n lanes amortized to an hourly rare, and the waiting cost, which refers to the cost of delays to the

calling population caused by traffic congestion on the road. Therefore, the expected cost *($/hr)* is given by

$$EC = nC_s + C_w L. \tag{7}$$

Minimizing *EC* in (7) is the objective of the optimization model in this section. The decision variables we adopt are the number of lanes, n, and the speed limit, v_1, as these are design parameters that can be controlled, in principle. When analysing the cost function in (7) as n and v_1, we observe that for lower speed limits, the probability of the road segment being full, P_c, is very high. In other words, there is a high chance that a driver will find the road "full," and will not be able to access the road. However, the cost function in (7) does not account for the cost of lost traffic, which could lead to optimal solutions, which are not reasonable. To avoid this, we add the service level constraint,

$$P_c \leq \alpha, \tag{8}$$

where the service level α denotes the acceptable fraction of lost demand. We find that values of α around 1% are reasonable. Constraint (8) is consistent with the Level of Service (LOS) terminology commonly used in the traffic literature (Mannering & Washburn, 2012), where a LOS of A indicates a free-flow state, and LOS of B, C, and D indicate acceptable congestion levels. LOS of E or F, indicate severe congestion, and potentially some drivers discontinuing their travel ("lost"). By incorporating constraint (8) into our model, we attempt to ensure that the system maintains an LOS between A and D. The different level of service are shown in Figure 3.

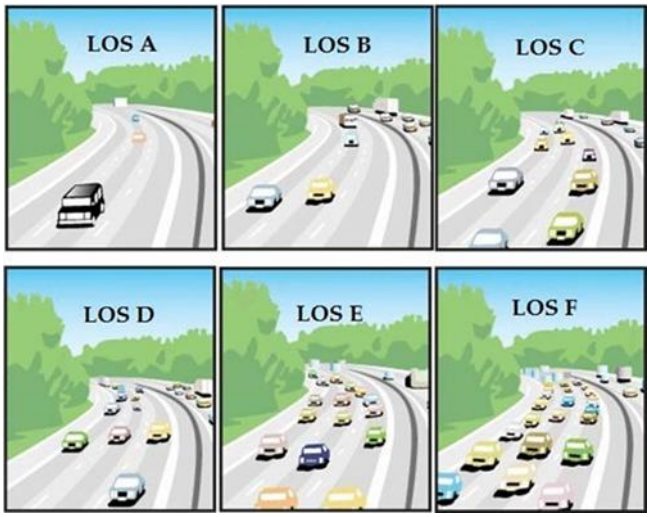

Figure 3. Different level of service (Amanamba, 2016)

Accordingly, our Road Cost Optimization model is formulated as follows,

$$\text{(RoCO)} \quad \min_{n, v_1} \quad (7)$$

subject to

$$(1), (3), (4), (5), (6), (8)$$

$$n \text{ integer}, \; v_1 \geq 0$$

3.3 Road Emission Optimization (RoEO Model)

In this section, we focus on modelling emissions. Let H(v) represent the quantity of CO_2 emissions produced per kilometer by a vehicle traveling at v km/h. Based on a least-squares fit analysis of data from the literature (Sbayti et al., 2002, Ntziachristos & Samaras, 2000, Alessandrini, et al., 2012), the following formula for H(v) was found to tb adequate,

$$H(v) = \frac{A}{v} + B \times v^m + C, \tag{9}$$

where A, B, m, and C are positive constants. The expected emissions (per hour) from vehicles traveling on the road segment can be estimated as $I \times L$, where L is the

average number of vehicles on the road segment as expressed in (6), and I denotes the average emissions per hour per vehicle present on the road. Noting that v_j is the amount of distance travelled in an hour by cars in State j, it can be seen that

$$I = \sum_{j=1}^{n} v_j H(v_j) P_j , \tag{10}$$

where v_j and P_j given in (2) and (3).

Assuming a "fixed" emission rate, E_c, associated with the construction of one lane of the road, the expected hourly emission (in Kg of CO_2 per hour) can be estimated, in a similar vein to the expected cost, EC, in Section 3.2, as

$$EE = nE_c + IL. \tag{11}$$

Utilizing the number of lanes and speed limit, again, as decision variables, our Road Emission Optimization model is formulated as follows.

$$\begin{aligned} &\text{(RoEO)} \quad \min_{n, v_1} \quad (11) \\ &\text{subject to} \\ &(1)-(6), (8)-(10) \\ &n \text{ integer}, v_1 \geq 0 \end{aligned}$$

3.4 Two-Objective Road Optimization

The objective of minimizing the expected emissions in (11) can be integrated with that of minimizing expected cost in (7) in two ways. First, by applying a carbon tax of C_t (per Kg of CO_2 emitted), we can define a total cost that accounts for the environmental impact as follows,

$$EC^e = EC + C_t EE, \tag{12}$$

where EC is given in (7). This results in the following Road Cost Optimization with Emission Consideration model,

$$\text{(RoCO-EC)} \quad \min_{n} \quad (12)$$

subject to

$$(1)-(6),(8)-(11)$$

n integer

One challenge with RoCO-EC is the difficulty in estimating the carbon tax, which tends to vary among different locations and fluctuate over time, while not capturing the full carbon effect. We discuss this in detail in Section 4.1. While we present the RoCO-EC model, for completeness, we advise against using it due to difficulties with the carbon tax. Instead, we recommend a second alternative based on multi-objective optimization. Our alternative two-objective optimization problem aims at balancing both cost and emissions by attempting to quantify the effect emissions in dollars. This model, which we refer to as Road Emission and Cost Optimization (RECO), is formulated as follows,

$$\text{(RECO)} \quad \min_{n,v_1} \quad (7)$$

$$\min_{n,v_1} \quad (11)$$

subject to

$$(1)-(6),\ (8)-(10)$$

n integer, $v_1 \geq 0$

CHAPTER 4

NUMERICAL ANALYSIS

This chapter presents the numerical analysis and results obtained. Section 4.1 highlights the parameter values and inputs used in the calculations. Section 4.2 presents the sensitivity of cost and emissions to key parameters. Section 4.3 outlines the results for different optimization models. Section 4.4 presents the trade-offs between cost and emissions, highlighting policy implications.

4.1 Parameter Estimation

We select our parameters values to reflect practical applications. The arrival rate of vehicles to the road segment, λ, ranges from 1,000 to 6,000 vehicles per hour (veh/h) with a base value of 4,000 veh/h. The jam density, *k,* ranges from 115 to 165 vehicles per lane-kilometer *(veh/lane-km),* with a base case assumption of 138 *veh/lane-km.* Both of these estimates are from Jain & Smith (1997). The speed limits were selected to be within 50 and 135 km/hr which is in-line with observed speed limits in the US, as shown in Figure 4.

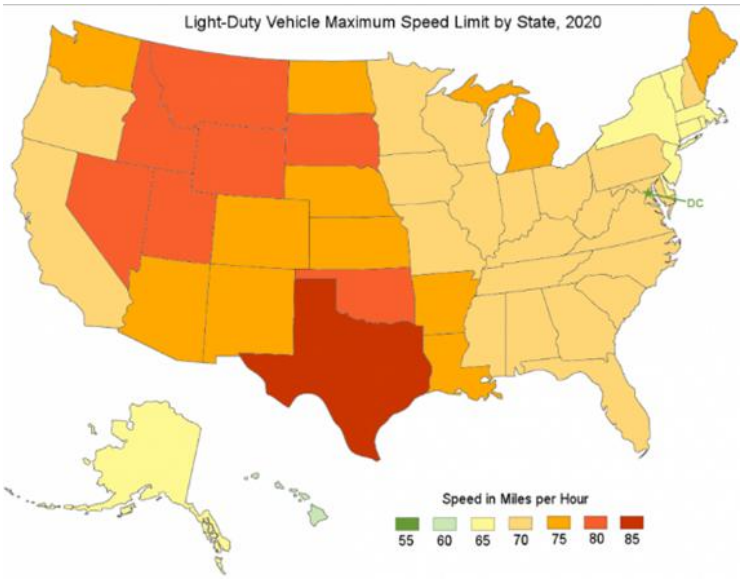

Figure 4. Speed Limits Across USA (FOTW, 2020)

As for the parameters of the cost model, the hourly cost of providing service, C_s, is calculated based on amortizing its cost over its expected lifespan *($/lane/km/h)*. Expanding highways in the US typically costs between $6 to $14 million per lane, per mile, including land acquisition (Litman, 2009), i.e., between $3.75 and $8.75 million per lane, per kilometer. Assuming a base value of $6.25 million, over a life time of 20 years, with a 0.5% monthly-compounded interest rate, the total cost of $6.25 million is equivalent equal monthly installments (Luenberger, 2014) given by,

$$(6.25\times10^{6})\frac{(0.005)}{1-1.005^{-240}}=\$44,780, \tag{13}$$

which, approximately, translates into an hourly cost of building a new lane of C_S = $62.19 per lane, per km. The cost of waiting, C_w, is estimated using the median hourly wage. According to the US Bureau of Labour Statistics, the median hourly wage is $34.51 BLS (2024).

To estimate hourly CO_2 emissions, the parameters of equation (9) are determined based on a least-squares fit to the data from Ntziachristos & Samaras (2000), yielding *A*

= 2663.43, $B = 2.12 \times 10^{-10}$, C =120.87, and m =5.48. Figure 5 illustrates how closely the model fits the data.

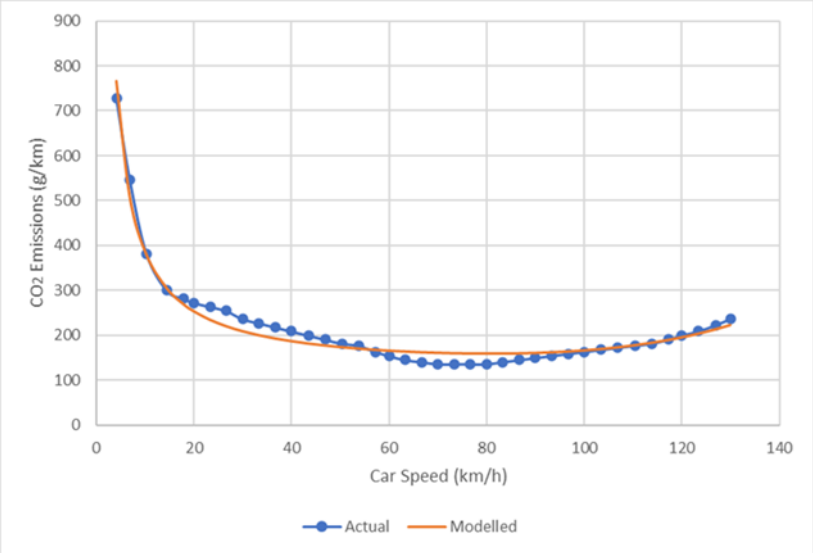

Figure 5. Actual vs modelled emissions function

Even though this model is used to estimate CO_2 emissions in particular, the constants can be calibrated to model other pollutant emissions, since all pollutants show a unimodal pattern. Our primary focus in this study is on CO_2 emissions due to its significant greenhouse effect (Ntziachristos & Samaras, 2000).

As for the carbon tax, C_t, its most recent value is 41$ cents for each tone of CO_2 based on the California cap-and-trade program (*CARB* 2024). The change in the carbon tax over time in California is depicted in Figure 6. This plot highlights the difficulty of accurately estimating the carbon tax, which complicates the estimation of the carbon emission cost in Model (ROCO-EC). This estimation is further complicated by the shared liability among the different stakeholders, such as car manufacturers, contractors, oil and gas companies, and passengers, all of whom bear a portion of the cost.

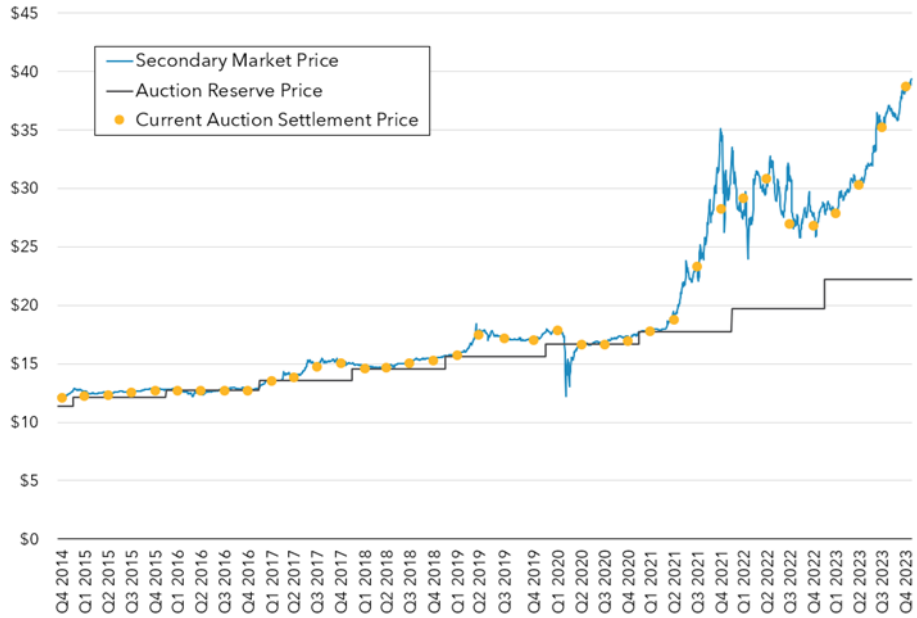

Figure 6. Change in the carbon tax over the years (CARB 2024).

Regarding the carbon emissions from the construction of one *lane-km* of highway, it is estimated that building a 4-lane, 1 *km* road would emit approximately 2,438.5 tons of CO_2 over its 20-year lifespan. This corresponds to an hourly emissions rate of approximately 3.47 kgCO_2 per *lane-km* (Park et al., 2003).

4.2 Sensitivity Analysis

In this section, we present the results of the sensitivity analysis for emissions and cost using the Top Rank software. The objective is to identify the effect of the accuracy parameter estimation (e.g. as done in Section 4.1) on the reliability of the model results. A tornado graph was plotted, by changing the parameters of the model from their base values in Section 4.1, for both cost and emissions to investigate the impact of the variables on their values. The tornado graphs presented in Figure 7 show that the total emissions are more sensitive to changes in the arrival rate than to changes in the vehicle speed limit. This indicates that the estimation of the arrival rate, l, should be handled with caution.

Furthermore, the tornado diagram presented in Figure 8 illustrates that cost is more sensitive to changing the arrival rate and the vehicle speed limit and compared to the cost of providing service and waiting cost. This suggests again high care in estimating the arrival rate l, and the speed limit, v_1. However, it is encouraging that little sensitivity is limited for the cost of providing service, C_s, and the waiting cost, C_w, as these costs might be difficult to estimate. The spider plots in Figures 9 and 10 confirm the findings.

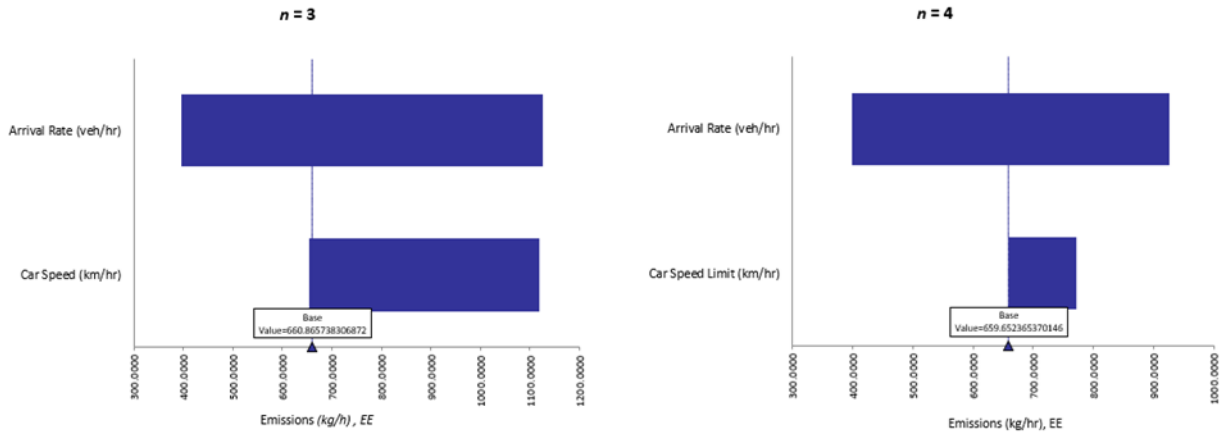

Figure 7. Tornado Graph for the Emissions for n = 3 and n = 4

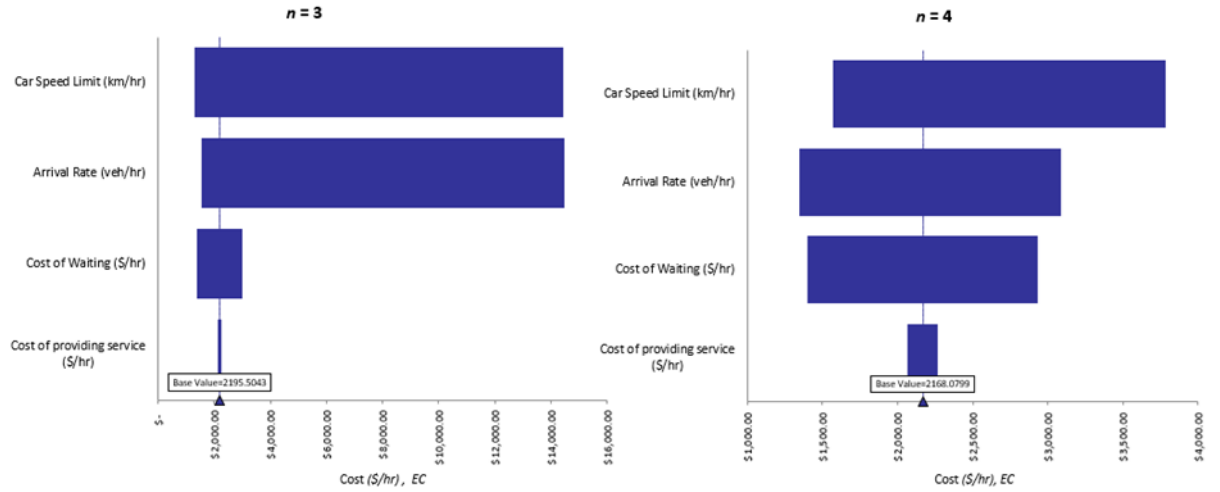

Figure 8. Tornado Graph for Costs for n = 3 and n = 4

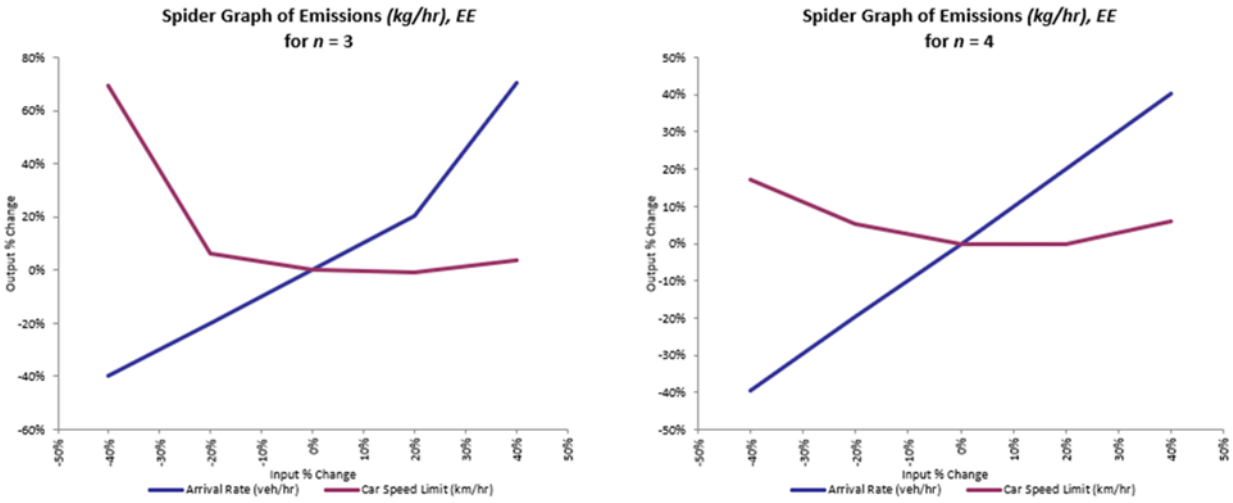

Figure 9. Spider Plot for Emissions for $n = 3$ and $n = 4$

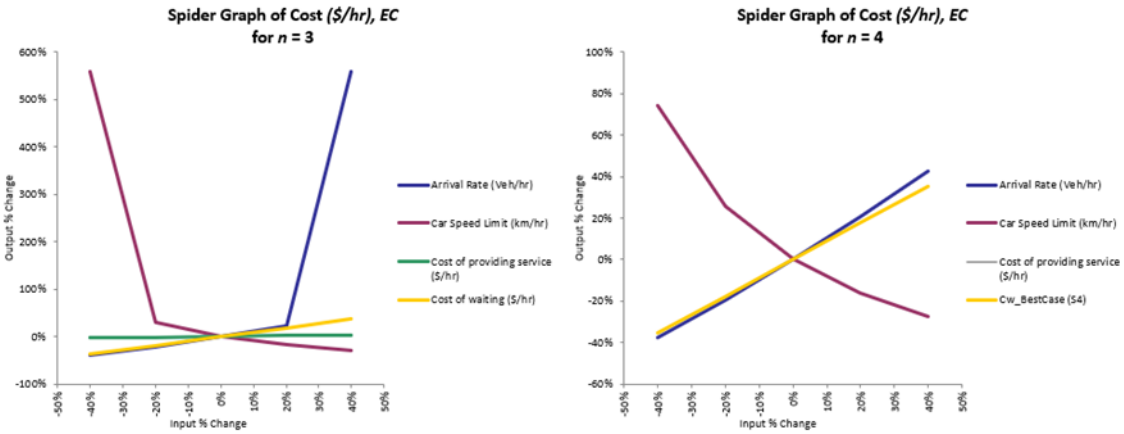

Figure 10. Spider Plot for Emissions for $n = 3$ and $n = 4$

4.3 Optimization over the Number of Lanes when the Speed Limit is Fixed

In this section, we apply the optimization models in Section 3. To simplify the analysis and presentation, we assume that the speed limit v_1 is fixed, and we consider the number of lanes, n, as the only decision variable. We begin by separately optimizing over cost and emission using models ROCO and RoEO, as described in Sections 3.2 and 3.3. The results are summarized in Table 1, where we present the optimal number of lanes that minimize cost, n_c*, and emissions, n_e*, along with their corresponding costs, $EC(n_c$*)

and $EC(n_e^*)$, respectively, and emissions, $EE(n_c^*)$ and $EE(n_e^*)$, respectively. The last two columns in Table 1 highlight the relative performance trade-offs between RoCO and RoEO in terms of cost and emissions. Specifically, the column before last reports $[EC(n_e^*) - EC(n_c^*)]/ EC(n_c^*)$, which measures the relative additional cost, aka "cost regret," of utilizing n_e^* instead of n_c^*. The final column reports, $[EE(n_c^*) - EE(n_e^*)]/ EE(n_c^*)$, which is a similar regret measure, but in terms of emissions.

Table 1. Optimization the cost and emissions over the number of lanes while varying the speed limit

Speed Limit, v_1 *(km/hr)*	**Optimization over Cost, Model RoCO**			**Optimization over Emissions, Model RoEO**			**Tradeoffs, RoCO vs. RoEO**	
	Optimal # of lanes, n_c^*	**Optimal Cost, $EC(n_c^*)$**	**Associated Emissions (kg/hr), $EE(n_c^*)$**	**Optimal # of lanes, n_e^***	**Optimal Emissions, $EE(n_e^*)$ (kg/hr)**	**Associated Cost, $EC(n_e^*)$**	**Cost Regret**	**Emission Reegret**
50	6	$3,470	745	7	744	$3,473	0.09%	0.15%
55	6	$3,154	721	7	721	$3,170	0.50%	0.01%
60	5	$2,892	704	6	703	$2,897	0.18%	0.12%
65	5	$2,668	688	5	688	$2,668	0%	0%
70	5	$2,481	676	5	676	$2,481	0%	0%
75	4	$2,314	667	4	667	$2,314	0%	0%
80	4	$2,168	660	4	660	$2,168	0%	0%
85	4	$2,042	655	3	655	$2,056	0.68%	0.12%
90	4	$1,932	655	3	652	$1,935	0.18%	-0.42%
95	3	$1,829	653	2	651	$1,917	4.57%	0.26%
100	3	$1,735	658	2	651	$1,802	3.69%	1.01%
105	3	$1,652	666	2	654	$1,702	2.92%	1.79%
110	3	$1,577	679	2	662	$1,613	2.23%	2.62%
115	3	$1,510	698	2	675	$1,535	1.61%	3.50%
120	3	$1,449	723	2	693	$1,464	1.05%	4.42%
125	3	$1,393	755	2	717	$1,401	0.53%	5.38%
130	3	$1,342	796	2	748	$1,343	0.05%	6.36%
135	2	$1,290	788	2	788	$1,290	0%	0%

We make the following observations based on Table 1.

1. The objectives of minimizing cost and emissions are not necessarily aligned, as reported by the different solutions for RoCO and RoEO. This is reflected in the different optimal number of lanes, n_c^* and n_e^*, and the corresponding costs and emissions in most of the cases presented in the Table 1. The penalty (regret) of

using one solution over the other can be substantial, e.g. reaching around 5% cost increase for a speed limit of 95 km/hr.

2. Optimizing over emissions generally results in a road design with (i) fewer lanes when the speed limit is high, e.g. above 95 km/hr in Table 1, and (ii) more lanes when the speed limit is low, e.g. below 65 km/hr in Table 1. This is an outcome of the unimodal relationship between emissions and speed. For example, for high-speed limits, the emissions minimization model, RoEO, pushes the system towards a lower average speed by utilizing a limited number of lanes.

Next, we explore the two-objective optimization model, RECO, presented in Section 3.4. With the number of lanes, *n*, as the only decision variable, we can efficiently solve the two-objective optimization model by enumerating different values of *n* and estimating the corresponding expected costs and emissions. Figure 11 summarizes this analysis for four speed limits: 60, 90, 105, and 135 *km/hr*. The main observation in Figure 11 is that the size of Pareto-optimal[1] (efficient) solution set is reduced as the speed limit increases. For instance, at a speed limit of 60 *km/hr*, the Pareto-optimal set consists of {5,6}. This set shifts to {3,4}, {2,3}, and {2}, respectively, for speed limits of 90, 105, and 135 *km/hr*. This behavior is again linked to the unimodal nature of emissions as a function of traveling speed, while cost decreases monotonically with increasing speed. Moderate speed limits lead to conflicting responses from the two objectives, affecting the optimal number of lanes and the feasible set of efficient solutions.

[1] A feasible number of lanes n_1 is a Pareto-efficient solution if there exists no other feasible solution n_2 such that $EC(n_2) \leq EC(n_1)$ and $EE(n_2) \leq EE(n_1)$, with at least one of the two inequalities being strict.

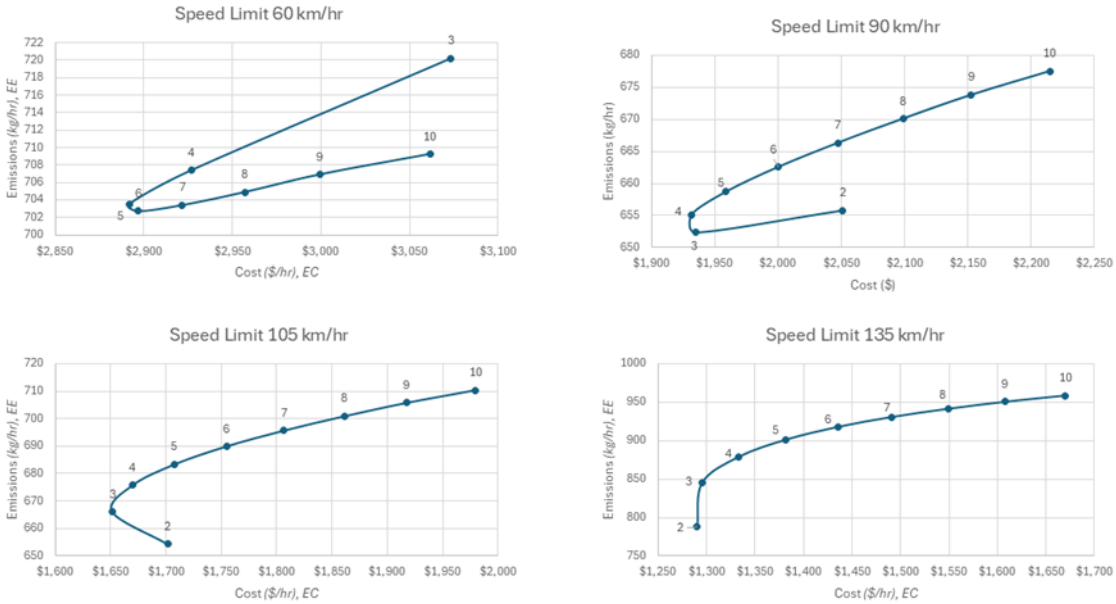

Figure 11. Emissions vs Cost for Different Speed Limits and Number of Lanes

4.4 Optimization over the Speed Limit when the Number of Lanes is fixed

In this section, we focus on the Pareto behavior of the RECO model to balance cost and emissions and identify efficient solutions that address the trade-offs between these two objectives. To simplify the analysis, we assume that the number of lanes, n, is given, and optimize over the speed limit v_1.

We begin by separately optimizing cost and emissions using the ROCO and ROEO models, similar to the analysis in Section 4.3. The results are presented in Table 2. In Table 2, we report the optimal speed limits that minimize cost and emissions, v_{1c}* and v_{1e}*, respectively, along with their corresponding cost, $EC(v_{1c}$*) and $EC(v_{1e}$*), respectively, and emissions, $EE(v_{1c}$*) and $EE(v_{1e}$*). We also report in the last three columns the relative performance (the trade-offs) of ROCO and ROEO in terms of cost and emissions regret, $[EC(v_{1e}$*) – $EC(v_{1c}$*)]/ $EC(v_{1c}$*) and $[EE(v_{1c}$*) – $EE(v_{1e}$*)]/ $EE(v_{1c}$*), similar to Table 1.

Table 2. Optimization the cost and emissions over the speed limit while varying the number of lanes

# of Lanes, n	Optimization over cost Model ROCO			Optimization over emissions Model ROEO			Trade offs ROCO vs ROEO	
	Optimal Speed Limit, v_{1c}^* *(km/hr)*	Optimal Cost, $EC(v_{1c}^*)$	Associated Emissions *(kg/hr)*, $EE(v_{1c}^*)$	Optimal Speed Limit, v_{1e}^* *(km/hr)*	Optimal Emissions (kg/hr), $EE(v_{1e}^*)$	Associated Cost, $EC(v_{1e}^*)$	Cost Regret	Emission Regret
2	120	$1,464	693	98	651	$1,846	26%	6%
3	120	$1,449	723	91	652	$1,913	32%	10%
4	120	$1,479	742	89	655	$1,952	32%	12%
5	120	$1,523	756	87	658	$2,021	33%	13%
6	120	$1,574	767	86	661	$2,080	32%	14%
7	120	$1,628	775	85	665	$2,147	32%	14%
8	120	$1,685	783	84	668	$2,219	32%	15%
9	120	$1,743	789	84	671	$2,271	30%	15%
10	120	$1,805	795	84	675	$2,334	29%	15%

Since cost decreases as speed increases, the optimal minimum cost is achieved at the highest speed limit of 120 *km/hr* for all the number of lanes. However, the optimal speed limit associated with the minimum emissions varies from 98 *km/hr* to 84 *km/hr*, as a result of the unimodal relation between speed and emissions discussed in Section 4.1. These speed limits are within the acceptable range of speed limits in the US (*FOTW #1156, 2020*).

To explore the Pareto efficiency of the solution, we introduce a new parameter, β, which varies incrementally from 0 to 20% with a 5% step increase, applied to the equation below,

$$EE_p \leq EE(v_{1e}^*)(1+\beta). \tag{14}$$

We then formulate the Road Emission and Cost Pareto Optimization (RECO-P) as

$$\text{(RECO-P)} \quad \min_{v_1} \quad (7)$$

subject to

$$(1)-(6),\ (8)-(10),(14)$$

$$v_1 \geq 0$$

Note that the solution methodology applies in (RECO-P) is a variation of the well-known e-constraint approach for solving multi-objective mathematical programming problems (see, for example, Chankong & Haimes, 2008 and Lin, 1976)

The calculations are performed using the base case values for all parameters, as given in Section 4.1. The results are displayed in Figure 12, which indicates interesting cost-emission trade-offs. For example, in a two-lane system, n = 2, a 5% increase above the emissions level (from 651 to 687.5 Kg CO_2/hr) leads to a 20% reduction in cost (from \$1,846 to \$1,500) compared to the optimal emissions solution. Furthermore, when emissions increase by 10%, the cost decreases by 30% for n greater or equal to 3, and when it increases by 15%, the cost drops by 40% for n greater or equal to 3. These results highlight the importance of trade-offs between cost and emissions in highway design, mainly that allowing a limited increase in emissions could lead to significant cost savings over adopting a strict policy geared solely at minimizing emissions.

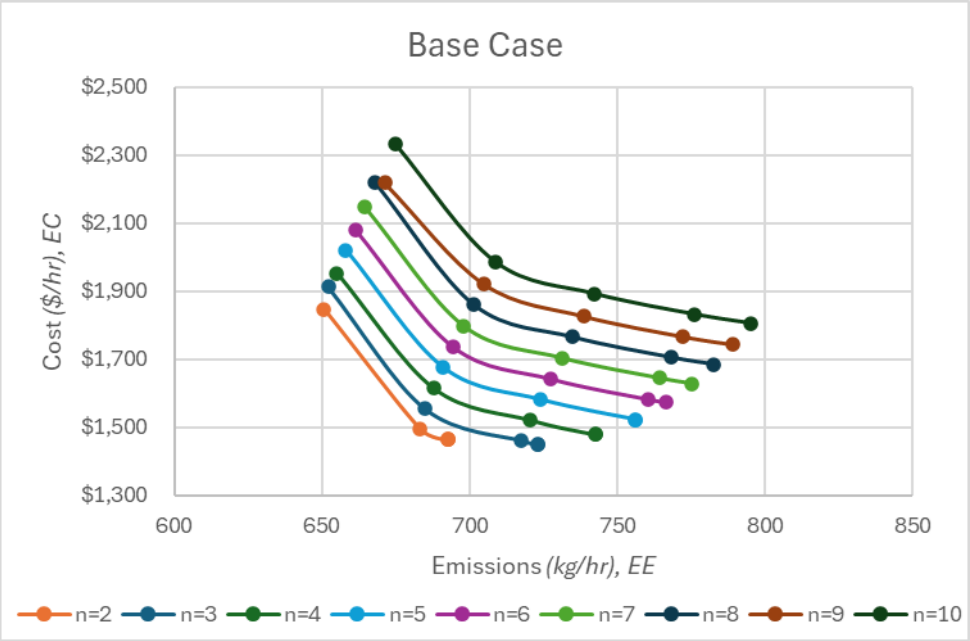

Figure 12. Pareto-Efficient Behavior - Base Case

The same analysis is repeated while varying the arrival rate from 1,000 to 6,000 vehicles per hour. (Accounting for the arrival variability rate is essential, as it is influenced by factors such as population growth and urban development, which can lead to higher traffic volumes over time.) The results presented in Figure 13 demonstrate a similar behavior, illustrating the trade-off on the efficient frontiers between cost and emissions. Slight increases in allowable emissions lead to significant cost reductions. It is important to note that for an arrival rate of 6000 *veh/hr*, a two-lane road is not a feasible option, as it fails to satisfy the service level requirement specified in constraint (8).

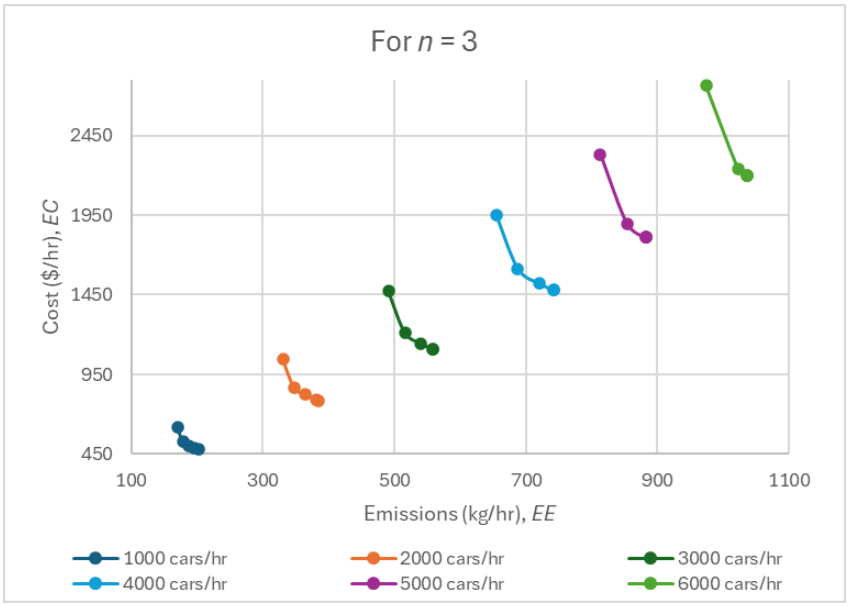

Figure 13a. Trade-offs Between Emissions and Associated Cost when Varying Arrival Rates for $n = 3$.

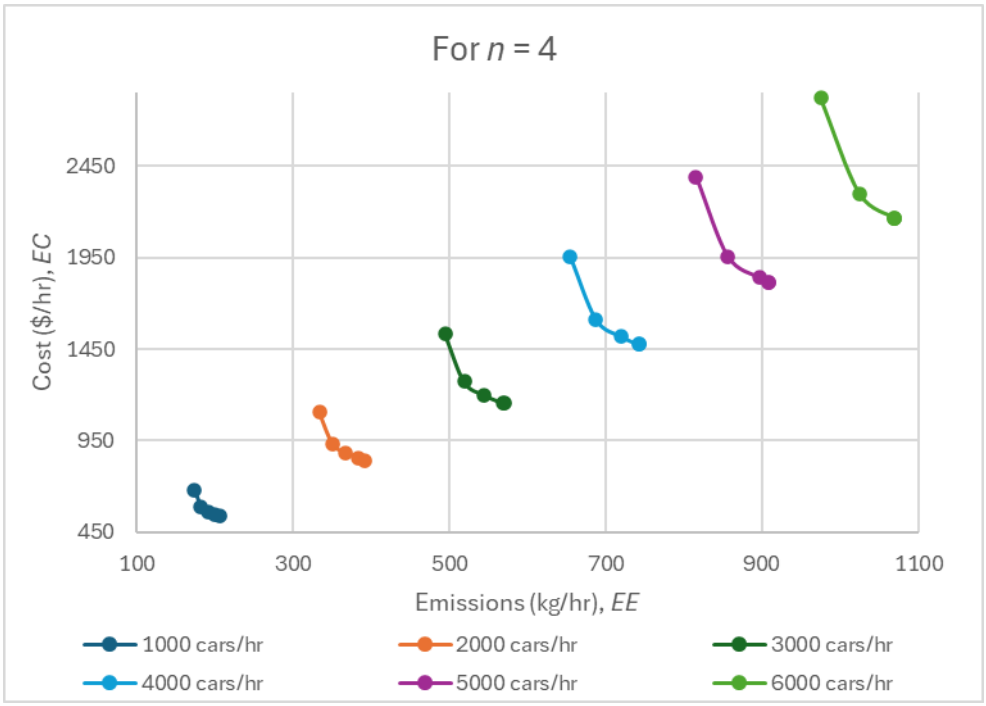

Figure 13b. Trade-offs Between Emissions and Associated Cost when Varying Arrival Rates for $n = 4$.

The same analysis is applied to the cost of providing service by varying C_s from a 20% decrease to a 20% increase. This allows understanding how economic factors such as resource availability and inflation, which influence the cost of providing service, affect

the road design. The results shown in Figure 14 are consistent with the results observed when varying the arrival rate. The results demonstrate again that a slight increase in the allowable emissions leads to a significant decrease in the cost. Finally, Figure 15 shows how the Pareto frontier behaves when the waiting cost, C_w, varies, which could reflect factors such as economic shifts, wage growth and inflation. A similar pattern is observed.

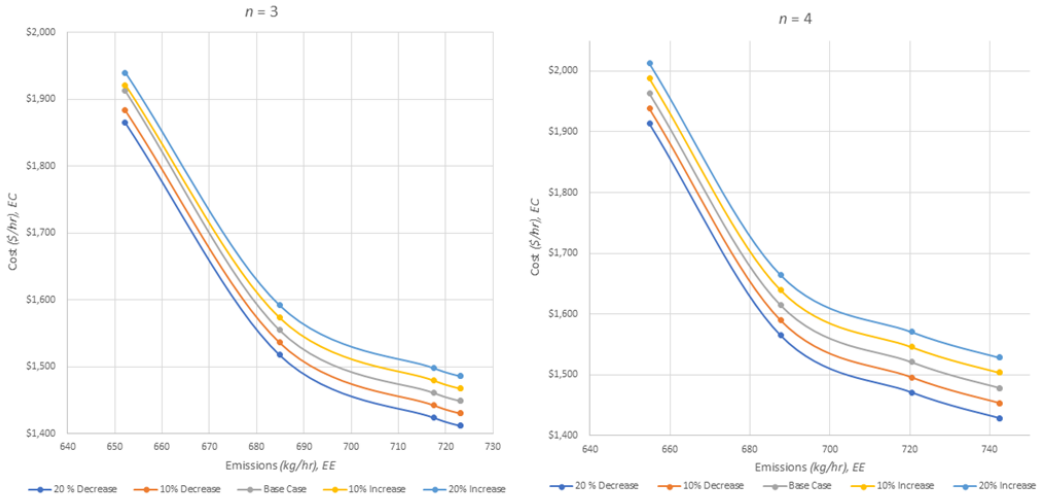

Figure 14. Trade-offs Between Emissions and Associated Cost when Varying the Cost of Providing Service

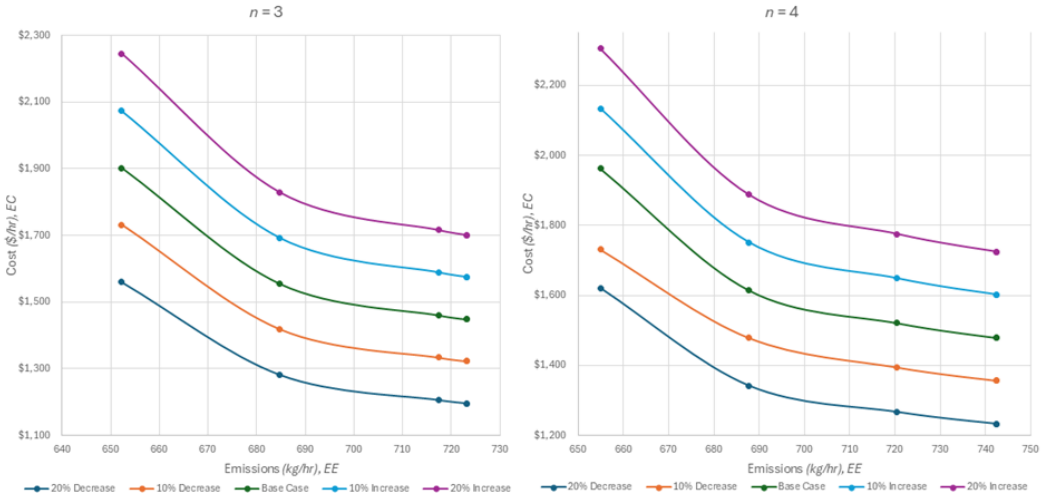

Figure 15. Trade-offs Between Emissions and Associated Cost when Varying the Cost of Waiting

A similar approach is applied for the jam capacity as it reflects the number of vehicles occupying a road segment. This analysis demonstrates the model's flexibility in adapting to mixed vehicle traffic, capturing realistic road usage scenarios across different regions and traffic compositions. The same trend is observed in Figure 16 with a key observation that the values differ slightly while varying the jam capacity.

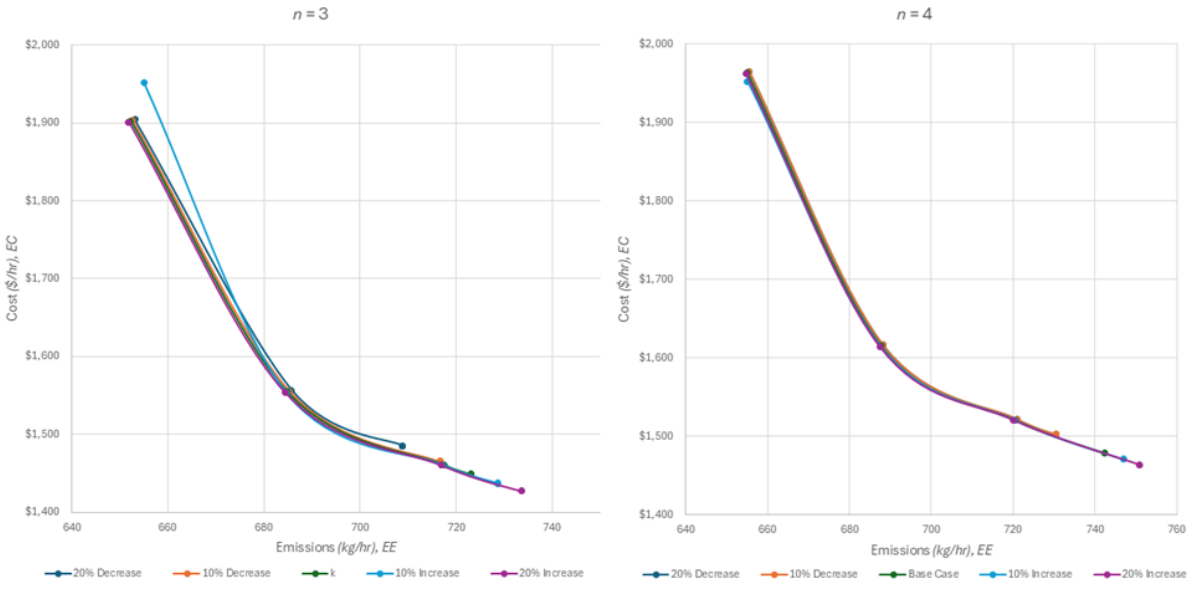

Figure 16. Trade-offs Between Emissions and Associated Cost when Varying the Jam Capacity

CHAPTER 5

CONCLUSION

In summary, this study develops a comprehensive cost model for highway systems that leverages queueing theory to address both environmental and financial impacts. By analyzing various traffic variables such as the number of lanes, speed limits, arrival rates, and jam capacity, the model offers valuable insights into the trade-offs between emissions and costs.

Our findings suggest that while minimizing emissions often leads to fewer lanes and moderate speeds, these decisions do not achieve the lowest costs, emphasizing the importance of analyzing Pareto-efficient trade-offs. Accordingly, trade-offs between cost and environmental impact must be carefully considered based on the specific objectives of road planning. Overall, this study provides the transportation sector with a framework for making strategic decisions that balance cost-effectiveness and sustainability in highway infrastructure development through practical and efficient operations management decisions, such as selecting the number of lanes or modifying the speed limit.

Future work could further improve the emissions model by integrating vehicle-specific factors, such as the reduced emissions from electric vehicles (EVs), and even hybrid vehicles. Moreover, the emissions model could be expanded to examine the impact of other pollutants, including nitrogen oxides (NO_x), carbon monoxide (CO), and hydrocarbon (HC). Lastly, this approach could be applied to other congestion-prone applications, such as port operations and internet server management.

APPENDIX 1

JUSTIFICATION OF THE LOS CONSTRAINT

The expected cost in (7) was calculated for various speed limits ranging from 50 *km/hr* to 135 *km/hr* and different number of lanes from 1 to 10. To highlight the impact of LOS constraint in equation (8) we run the model by excluding the constraint.). The results are presented graphically in Figure A1.

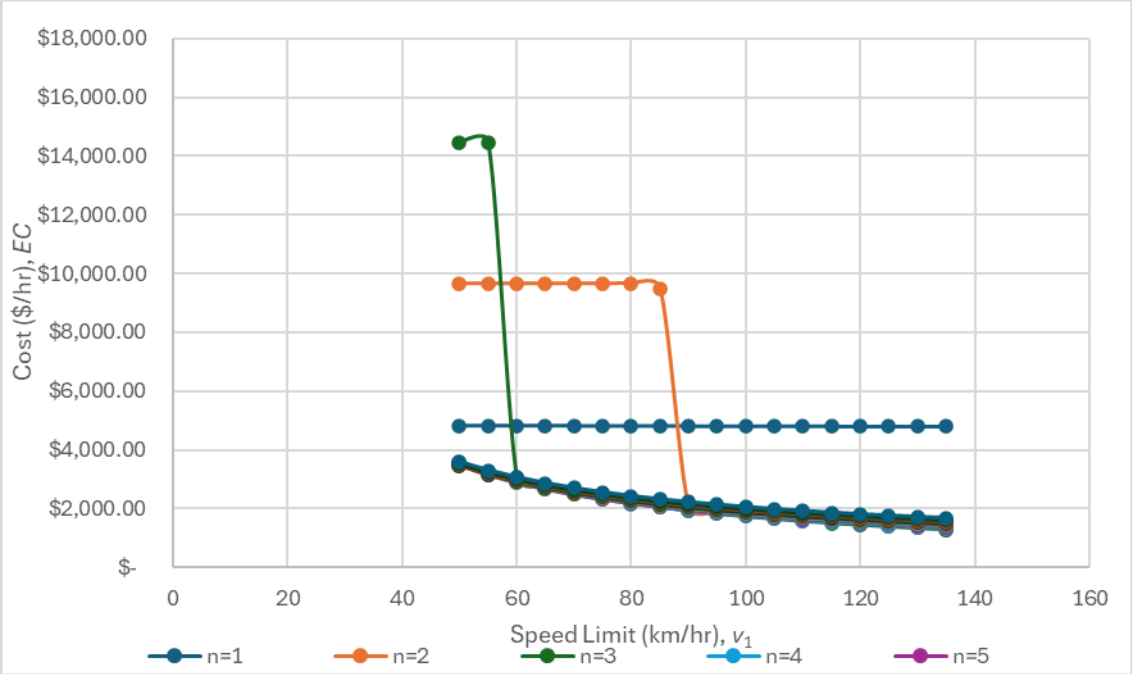

Figure A1. Cost vs Speed Limit for Different Numbers of Lanes

Examining Figure A1, we observe that for a single lane, $n = 1$, the LOS constraint is most likely not satisfied, for reasonable values of α, as the cost is not affected by the speed limit, indicating that the system is full for all possible speed limits. Similarly, for $n = 2$ and $n = 3$, and for speed limits less than 90 and 60 km/hr, respectively, the constraint is not satisfied. For speed limits slightly above 90 and 60 km/hr for n = 2 and 3, respectively, there is a sharp decrease in cost, apparently as a result from a drop in congestion, as a higher speed limit increases the service rate, and the LOS constraint

holds. This effect is further illustrated In Figure A.2, which shows the system size probability for different numbers of lanes at a speed limit of v_1 = 70 *km/hr*.

In the single-lane system (top left of Figure A.2), where c = 138, the rejection probability P_c approaches 1. This indicates that this system is almost always full, causing severe congestion and high waiting cost. When the number of lanes increases to n = 2 (top right plot of Figure A.2), the rejection probability drops to around 2%. Although it is still relatively high, it is sufficient to reduce the waiting cost, as reflected in Figure A.3.

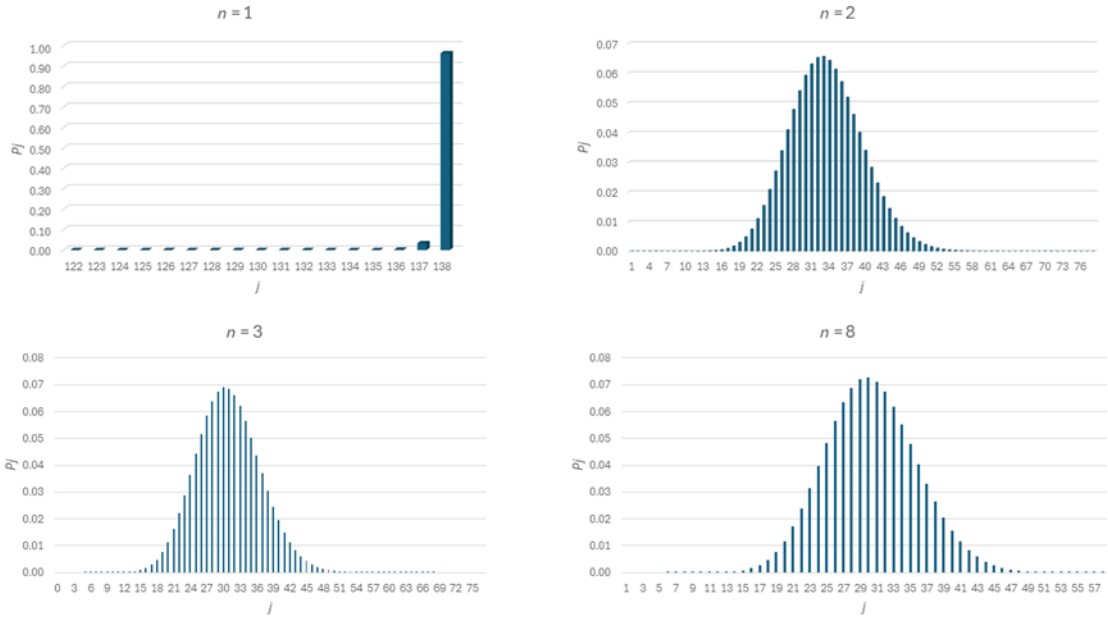

Figure A2. System Size Probabilities for Different Numbers of Lanes, n, and a Speed Limit $\boldsymbol{v_1}$ = 70 km/hr

Therefore, the importance of our LOS constraint in (8) becomes clear. For the remainder of the results, we set $\alpha = 1\%$ to ensure that the level of service remains between A and D. After applying Constraint (8), the revised results are displayed in Figure A3, which omits scenarios where the LOS constraint is not met. Specifically, the case of only one lane, n = 1, is excluded, as well as scenarios with 2 and 3 lanes at lower speeds.

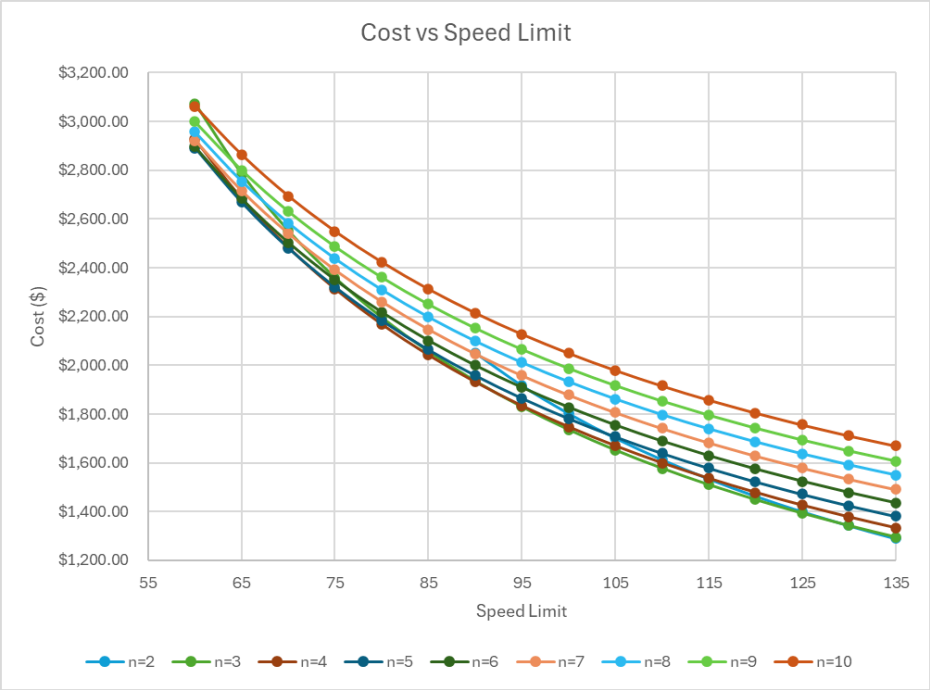

Figure A3. Cost vs Speed Limit for Different Numbers of Lanes after applying constraint (8)

APPENDIX 2

DETAILED PARETO ANALYSIS RESULTS

In this appendix, we present the detailed results used from the Pareto Analysis in Section 4.3.

a) Base Case

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
# of Lanes, *n*	**Optimal Emissions (kg/hr), *EE(v_{1e}*)***	**Optimal Speed Limit, *v_{1e}* (km/hr)***	**Associated Cost, *EC(v_{1e}*)***	***β***	**Target Emissions (kg/hr)**	**Associated Emissions *(kg/hr), EE(v_{1c}*)***	**Associated Speed Limit, *v_{1c}* (km/hr)***	**Optimal Cost, *EC(v_{1c}*)***	**Change in Emissions**	**Change in Speed**	**Change in Cost**
2	**650.69**	**98**	**$1,846**	0%	650.69	650.69	98	$1,846	0%	0%	0%
				5%	683.23	683.23	118	$1,497	5%	20%	-19%
				10%	715.76	692.53	120	$1,464	6%	22%	-21%

				15%	748.30	692.53	120	$1,464	6%	22%	-21%
				20%	780.83	692.53	120	$1,464	6%	22%	-21%
3	**652.22**	**91**	**$ 1,913**	0%	652.22	652.22	91	$1,913	0%	0%	0%
				5%	684.83	684.83	112	$ 1,555	5%	23%	-19%
				10%	717.44	717.44	119	$1,461	10%	31%	-24%
				15%	750.06	723.17	120	$1,449	11%	32%	-24%
				20%	782.67	723.17	120	$1,449	11%	32%	-24%
4	**654.98**	**89**	**$ 1,952**	0%	654.98	654.98	89	$1,952	0%	0%	0%
				5%	687.73	687.73	109	$1,615	5%	22%	-17%
				10%	720.48	720.48	116	$1,521	10%	31%	-22%
				15%	753.23	742.43	120	$1,479	13%	35%	-24%
				20%	785.98	742.43	120	$1,479	13%	35%	-24%
5	**658.07**	**87**	**$ 2,021**	0%	658.07	658.07	87	$2,021	0%	0%	0%
				5%	690.97	690.97	107	$1,676	5%	23%	-17%
				10%	723.88	723.88	115	$1,582	10%	32%	-22%

				15%	756.78	756.03	120	$1,523	15%	38%	-25%
				20%	789.68	756.03	120	$1,523	15%	38%	-25%
6	**661.32**	**86**	**$ 2,080**	0%	661.32	661.32	86	$2,080	0%	0%	0%
				5%	694.38	694.38	106	$1,737	5%	24%	-17%
				10%	727.45	727.45	114	$1,643	10%	32%	-21%
				15%	760.51	760.52	119	$1,583	15%	39%	-24%
				20%	793.58	766.53	120	$1,574	16%	40%	-24%
7	**664.63**	**85**	**$ 2,147**	0%	664.63	664.63	85	$2,147	0%	0%	0%
				5%	697.86	697.86	106	$1,798	5%	24%	-16%
				10%	731.10	731.10	113	$1,704	10%	33%	-21%
				15%	764.33	764.33	119	$1,644	15%	39%	-23%
				20%	797.56	775.15	120.00	$1,628	17%	41%	-24%
8	**668.01**	**84**	**$ 2,219**	0%	668.01	668.01	84	$2,219	0%	0%	0%
				5%	701.41	701.41	105	$1,859	5%	25%	-16%
				10%	734.81	734.81	113	$1,765	10%	34%	-20%

				15%	768.21	768.21	118	$1,705	15%	41%	-23%
				20%	801.61	782.56	120	$1,685	17%	43%	-24%
9	**671.38**	**84**	**$ 2,219**	0%	671.38	671.38	84	$2,219	0%	0%	0%
				5%	704.95	704.95	105	$1,921	5%	25%	-13%
				10%	738.52	738.52	112	$1,826	10%	34%	-18%
				15%	772.09	772.09	118	$1,767	15%	40%	-20%
				20%	805.66	789.13	120	$1,743	18%	43%	-21%
10	**674.80**	**84**	**$ 2,334**	0%	674.80	674.80	84	$2,337	0%	0%	0%
				5%	708.54	708.54	104	$1,987	5%	24%	-15%
				10%	742.28	742.28	112	$1,892	10%	33%	-19%
				15%	776.02	776.02	117	$1,831	15%	40%	-22%
				20%	809.76	795.11	120	$1,805	18%	43%	-23%

b) Arrival Rate, λ

i) For $n = 3$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Arrival Rate, λ *(Veh/hr)*	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* *(km/hr)***	**Associated Cost, $EC(v_{1e}^*)$**	***β***	**Target Emissions *(kg/hr)***	**Associated Emissions *(kg/hr)*, $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* *(km/hr)***	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
1000	**171**	**83**	**615**	0%	171	171	83	615	0%	0%	0%
				5%	179	179	104	527	5%	25%	-14%
				10%	188	188	111	503	10%	34%	-18%
				15%	196	196	117	488	15%	41%	-21%
				20%	205	202	120	480	18%	45%	-22%
2000	**331**	**86**	**1044**	0%	331	331	86	1044	0%	0%	0%

				5%	348	348	106	869	5%	24%	-17%
				10%	364	364	114	822	10%	33%	-21%
				15%	381	381	119	792	15%	39%	-24%
				20%	397	384	120	787	16%	40%	-25%
3000	**492**	**88**	**1473**	0%	492	492	88	1473	0%	0%	0%
				5%	516	516	109	1212	5%	23%	-18%
				10%	541	541	116	1142	10%	31%	-23%
				15%	565	558	120	1109	13%	36%	-25%
				20%	590	558	120	1109	13%	36%	-25%
4000	**655**	**89**	**1952**	0%	655	655	89	1952	0%	0%	0%
				5%	688	688	109	1615	5%	22%	-17%
				10%	720	720	116	1521	10%	31%	-22%
				15%	753	742	120	1479	13%	35%	-24%
				20%	786	742	120	1479	13%	35%	-24%
5000	**813**	**95**	**2332**	0%	813	813	95	2332	0%	0%	0%

				5%	854	854	115	1898	5%	21%	-19%
				10%	894	882	120	1809	8%	27%	-22%
				15%	935	882	120	1809	8%	27%	-22%
				20%	976	882	120	1809	8%	27%	-22%
6000	**974**	**98**	**2762**	0%	974	974	98	2762	0%	0%	0%
				5%	1023	1023	118	2241	5%	20%	-19%
				10%	1071	1036	120	2196	6%	22%	-20%
				15%	1120	1036	120	2196	6%	22%	-20%
				20%	1169	1036	120	2196	6%	22%	-20%

ii) For $n = 4$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Arrival Rate, λ *(Veh/hr)*	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* *(km/hr)***	**Associated Cost, $EC(v_{1e}^*)$**	***β***	**Target Emissions *(kg/hr)***	**Associated Emissions *(kg/hr)*, $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* *(km/hr)***	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
1000	**174**	**82**	**$677**	0%	174	174	82	$677	0%	0%	0%
				5%	183	183	104	$588	5%	26%	-13%
				10%	191	191	111	$564	10%	35%	-17%
				15%	200	200	117	$549	15%	42%	-19%
				20%	209	207	120	$541	19%	46%	-20%
2000	**334**	**84**	**$1,106**	0%	334	334	84	$1106	0%	0%	0%

				5%	351	351	105	$930	5%	25%	-16%
				10%	368	368	113	$883	10%	33%	-20%
				15%	384	384	118	$853	15%	40%	-23%
				20%	401	392	120	$842	17%	42%	-24%
3000	**495**	**86**	**$1,534**	0%	495	495	86	$1534	0%	0%	0%
				5%	519	519	107	$1273	5%	24%	-17%
				10%	544	544	114	$1202	10%	32%	-22%
				15%	569	569	120	$1157	15%	39%	-25%
				20%	594	570	120	$1155	15%	39%	-25%
4000	**655**	**89**	**$1,952**	0%	655	655	89	$1952	0%	0%	0%
				5%	688	688	109	$1615	5%	22%	-17%
				10%	720	720	116	$1521	10%	31%	-22%
				15%	753	742	120	$1479	13%	35%	-24%
				20%	786	742	120	$1479	13%	35%	-24%
5000	**815**	**91**	**$2,392**	0%	815	815	91	$2392	0%	0%	0%

				5%	856	856	111	$1957	5%	22%	-18%
				10%	897	897	118	$1840	10%	30%	-23%
				15%	938	909	120	$1816	11%	32%	-24%
				20%	978	909	120	$1816	11%	32%	-24%
6000	**976**	**93**	**$2,821**	0%	976	976	93	$2821	0%	0%	0%
				5%	1025	1025	113	$2300	5%	22%	-18%
				10%	1073	1070	120	$2168	10%	29%	-23%
				15%	1122	1070	120	$2168	10%	29%	-23%
				20%	1171	1070	120	$2168	10%	29%	-23%

c) Cost of providing Service, C_s

i) For $n = 3$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Cost of Providing Service, C_S	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* (km/hr)**	**Associated Cost, $EC(v_{1e}^*)$**	**β**	**Target Emissions (kg/hr)**	**Associated Emissions (kg/hr), $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* (km/hr)**	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20 % Decrease	**652**	**91**	**$1,865**	0%	652	652	91	$1,865	0%	0%	0%
				5%	685	685	112	$1,518	5%	22%	-19%
				10%	717	717	119	$1,424	10%	30%	-24%
				15%	750	723	120	$1,411	11%	31%	-24%
				20%	783	723	120	$1,411	11%	31%	-24%
10% Decrease	**652**	**91**	**$1,884**	0%	652	652	91	$1,884	0%	0%	0%
				5%	685	685	112	$1,536	5%	22%	-18%

				10%	717	717	119	$1,442	10%	30%	-23%
				15%	750	723	120	$1,430	11%	31%	-24%
				20%	783	723	120	$1,430	11%	31%	-24%
Base Case $62.19	**652**	**91**	**$1,913**	0%	652	652	91	$1,913	0%	0%	0%
				5%	685	685	112	$1,555	5%	22%	-19%
				10%	717	717	119	$1,461	10%	30%	-24%
				15%	750	723	120	$1,449	11%	31%	-24%
				20%	783	723	120	$1,449	11%	31%	-24%
10% Increase	**652**	**91**	**$1,921**	0%	652	652	91	$1,921	0%	0%	0%
				5%	685	685	112	$ 1,574	5%	22%	-18%
				10%	717	717	119	$1,480	10%	30%	-23%
				15%	750	723	120	$1,467	11%	31%	-24%
				20%	783	723	120	$1,467	11%	31%	-24%
20% Increase	**652**	**91**	**$1,940**	0%	652	652	91	$1,940	0%	0%	0%
				5%	685	685	112	$1,592	5%	22%	-18%

				10%	717	717	119	$1,498	10%	30%	-23%
				15%	750	723	120	$1,486	11%	31%	-23%
				20%	783	723	120	$1,486	11%	31%	-23%

ii) For $n = 4$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Cost of Providing Service, C_S	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* (km/hr)**	**Associated Cost, $EC(v_{1e}^*)$**	**β**	**Target Emissions (kg/hr)**	**Associated Emissions (kg/hr), $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* (km/hr)**	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20 % Decrease	**655**	**89**	**$1,913**	0%	655	655	89	$1,913	0%	0%	0%
				5%	688	688	109	$1,565	5%	23%	-18%
				10%	720	720	116	$1,471	10%	31%	-23%

				15%	753	742	120	$1,429	13%	36%	-25%
				20%	786	742	120	$1,429	13%	36%	-25%
10% Decrease	**655**	**89**	**$1,938**	0%	655	655	89	$1,938	0%	0%	0%
				5%	688	688	109	$1,590	5%	23%	-18%
				10%	720	720	116	$1,496	10%	31%	-23%
				15%	753	742	120	$1,454	13%	36%	-25%
				20%	786	742	120	$1,454	13%	36%	-25%
Base Case	**655**	**89**	**$1,963**	0%	655	655	89	$1,963	0%	0%	0%
				5%	688	688	109	$1,615	5%	23%	-18%
				10%	720	720	116	$1,521	10%	31%	-23%
				15%	753	742	120	$1,479	13%	36%	-25%
				20%	786	742	120	$1,479	13%	36%	-25%
10% Increase	**655**	**89**	**$1,988**	0%	655	655	89	$1,988	0%	0%	0%
				5%	688	688	109	$1,640	5%	23%	-18%
				10%	720	720	116	$1,546	10%	31%	-22%
				15%	753	742	120	$1,504	13%	36%	-24%

				20%	786	742	120	$1,504	13%	36%	-24%
20% Increase	**655**	**89**	**$2,013**	0%	655	655	89	$2,013	0%	0%	0%
				5%	688	688	109	$1,665	5%	23%	-17%
				10%	720	720	116	$1,571	10%	31%	-22%
				15%	753	742	120	$1,528	13%	36%	-24%
				20%	786	742	120	$1,528	13%	36%	-24%

d) Cost of Waiting, C_w

i) For n = 3

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Cost of Waiting, C_W	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* (km/hr)**	**Associated Cost, $EC(v_{1e}^*)$**	**β**	**Target Emissions (kg/hr)**	**Associated Emissions (kg/hr), $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* (km/hr)**	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20% Decrease	**652.21**	**91.47**	**$1,559.33**	0%	652.21	652.21	91.47	$1,559.33	0%	0%	0%
				5%	684.82	684.82	111.60	$1,281.22	5%	22%	-18%
				10%	717.43	717.43	118.96	$1,206.06	10%	30%	-23%
				15%	750.04	723.17	120.00	$1,196.30	11%	31%	-23%
				20%	782.65	723.17	120.00	$1,196.30	11%	31%	-23%
10% Decrease	**652.21**	**91.47**	**$1,730.92**	0%	652.21	652.21	91.47	$1,730.92	0%	0%	0%
				5%	684.82	684.82	111.60	$1,418.06	5%	22%	-18%

				10%	717.43	717.43	118.96	$1,333.50	10%	30%	-23%
				15%	750.04	723.17	120.00	$1,322.52	11%	31%	-24%
				20%	782.65	723.17	120.00	$1,322.52	11%	31%	-24%
Base Case	**652.21**	**91.47**	**$1,902.51**	0%	652.21	652.21	91.47	$1,902.51	0%	0%	0%
				5%	684.82	684.82	111.60	$1,554.89	5%	22%	-18%
				10%	717.43	717.43	118.96	$1,460.93	10%	30%	-23%
				15%	750.04	723.17	120.00	$1,448.73	11%	31%	-24%
				20%	782.65	723.17	120.00	$1,448.73	11%	31%	-24%
10% Increase	**652.21**	**91.47**	**$2,074.11**	0%	652.21	652.21	91.47	$2,074.11	0%	0%	0%
				5%	684.82	684.82	111.60	$1,691.72	5%	22%	-18%
				10%	717.43	717.43	118.96	$1,588.37	10%	30%	-23%
				15%	750.04	723.17	120.00	$1,574.95	11%	31%	-24%
				20%	782.65	723.17	120.00	$1,574.95	11%	31%	-24%
20% Increase	**652.21**	**91.47**	**$2,245.70**	0%	652.21	652.21	91.47	$2,245.70	0%	0%	0%
				5%	684.82	684.82	111.60	$1,828.55	5%	22%	-19%

				10%	717.43	717.43	118.96	$1,715.81	10%	30%	-24%
				15%	750.04	723.17	120.00	$1,701.17	11%	31%	-24%
				20%	782.65	723.17	120.00	$1,701.17	11%	31%	-24%

ii) For $n = 4$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Cost of Waiting, C_W	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* (km/hr)**	**Associated Cost, $EC(v_{1e}^*)$**	**β**	**Target Emissions (kg/hr)**	**Associated Emissions (kg/hr), $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* (km/hr)**	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20% Decrease	**654.96**	**88.51**	**$1,620.16**	0%	654.96	654.96	88.51	$1,620.16	0%	0%	0%
				5%	687.71	687.71	108.86	$1,341.73	5%	23%	-17%
				10%	720.46	720.46	116.28	$1,266.58	10%	31%	-22%
				15%	753.21	742.43	120.00	$1,232.68	13%	36%	-24%

				20%	785.96	742.43	120.00	$1,232.68	13%	36%	-24%
10% Decrease	**654.96**	**88.51**	**$1,730.92**	0%	654.96	654.96	88.51	$1,730.92	0%	0%	0%
				5%	687.71	687.71	108.86	$1,478.35	5%	23%	-15%
				10%	720.46	720.46	116.28	$1,393.80	10%	31%	-19%
				15%	753.21	742.43	120.00	$1,355.68	13%	36%	-22%
				20%	785.96	742.43	120.00	$1,355.68	13%	36%	-22%
Base Case	**654.96**	**88.51**	**$1,963.00**	0%	654.96	654.96	88.51	$1,963.00	0%	0%	0%
				5%	687.71	687.71	108.86	$1,614.97	5%	23%	-18%
				10%	720.46	720.46	116.28	$1,521.03	10%	31%	-23%
				15%	753.21	742.43	120.00	$1,478.67	13%	36%	-25%
				20%	785.96	742.43	120.00	$1,478.67	13%	36%	-25%
10% Increase	**654.96**	**88.51**	**$2,134.43**	0%	654.96	654.96	88.51	$2,134.43	0%	0%	0%
				5%	687.71	687.71	108.86	$1,751.59	5%	23%	-18%
				10%	720.46	720.46	116.28	$1,648.26	10%	31%	-23%
				15%	753.21	742.43	120.00	$1,601.66	13%	36%	-25%

				20%	785.96	742.43	120.00	$1,601.66	13%	36%	-25%
20% Increase	**654.96**	**88.51**	**$2,305.85**	0%	654.96	654.96	88.51	$2,305.85	0%	0%	0%
				5%	687.71	687.71	108.86	$1,888.21	5%	23%	-18%
				10%	720.46	720.46	116.28	$1,775.49	10%	31%	-23%
				15%	753.21	742.43	120.00	$1,724.65	13%	36%	-25%
				20%	785.96	742.43	120.00	$1,724.65	13%	36%	-25%

e) Jam Capacity, *j*

i) For *n* = 3

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Jam Capacity, *k*	**Optimal Emissions (kg/hr), $EE(v_{1e}^*)$**	**Optimal Speed Limit, v_{1e}^* *(km/hr)***	**Associated Cost, $EC(v_{1e}^*)$**	**β**	**Target Emissions *(kg/hr)***	**Associated Emissions *(kg/hr)*, $EE(v_{1c}^*)$**	**Associated Speed Limit, v_{1c}^* *(km/hr)***	**Optimal Cost, $EC(v_{1c}^*)$**	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20% Decrease	**653.08**	**94.64**	**$1,904.38**	0%	653.08	653.08	94.64	$1,904.38	0%	0%	0%
				5%	685.73	685.73	114.55	$1,556.53	5%	21%	-18%
				10%	718.39	708.82	120.00	$1,484.98	9%	27%	-22%
				15%	751.04	708.82	120.00	$1,484.98	9%	27%	-22%
				20%	783.70	708.82	120.00	$1,484.98	9%	27%	-22%
10% Decrease	**652.57**	**92.85**	**$1,903.33**	0%	652.57	652.57	92.85	$1,903.33	0%	0%	0%
				5%	685.20	685.20	112.89	$1,555.59	5%	22%	-18%

				10%	717.83	716.61	120.00	$1,464.30	10%	29%	-23%
				15%	750.46	716.61	120.00	$1,465.30	10%	29%	-23%
				20%	783.09	716.61	120.00	$1,466.30	10%	29%	-23%
Base Case	**652.21**	**91.47**	**$1,902.51**	0%	652.21	652.21	91.47	$1,902.51	0%	0%	0%
				5%	684.82	684.82	111.60	$1,554.89	5%	22%	-18%
				10%	717.43	717.43	118.96	$1,460.93	10%	30%	-23%
				15%	750.04	723.17	120.00	$1,448.73	11%	31%	-24%
				20%	782.65	723.17	120.00	$1,449.73	11%	31%	-24%
10% Increase	**651.93**	**90.37**	**$1,901.87**	0%	651.93	654.98	89.00	$1,952.48	0%	-2%	3%
				5%	684.53	684.53	110.57	$1,554.34	5%	22%	-18%
				10%	717.13	717.13	117.95	$1,460.43	10%	31%	-23%
				15%	749.72	728.75	120.00	$1,436.59	12%	33%	-24%
				20%	782.32	728.75	120.00	$1,437.59	12%	33%	-24%
20% Increase	**651.72**	**89.47**	**$1,901.36**	0%	651.72	651.72	89.47	$1,901.36	0%	0%	0%
				5%	684.30	684.30	109.73	$1,553.91	5%	23%	-18%

				10%	716.89	716.89	117.12	$1,460.03	10%	31%	-23%
				15%	749.47	733.54	120.00	$1,426.84	13%	34%	-25%
				20%	782.06	733.54	120.00	$1,427.84	13%	34%	-25%

ii) For $n = 4$

Optimization over emissions Model RoEO				**Optimization over cost Model RoCO**					**Trade offs RoCO vs RoEO**		
Jam Capacity, *k*	**Optimal Emissions (kg/hr), *EE(v_{1e}*)***	**Optimal Speed Limit, *v_{1e}**** ***(km/hr)***	**Associated Cost, *EC(v_{1e}*)***	***β***	**Target Emissions *(kg/hr)***	**Associated Emissions *(kg/hr), EE(v_{1c}*)***	**Associated Speed Limit, *v_{1c}**** ***(km/hr)***	**Optimal Cost, *EC(v_{1c}*)***	**Change in Emissions**	**Change in Speed**	**Change in Cost**
20% Decrease	**655.49**	**90.71**	**$1,964.26**	0%	655.49	655.49	90.71	$1,964.26	0%	0%	0%
				5%	688.26	688.26	110.94	$1,616.03	5%	22%	-18%
				10%	721.03	721.03	118.33	$1,522.01	10%	30%	-23%
				15%	753.81	730.45	120.00	$1,502.52	11%	32%	-24%
				20%	786.58	730.45	120.00	$1,502.52	11%	32%	-24%
10% Decrease	**655.19**	**89.47**	**$1,963.55**	0%	655.19	655.19	89.47	$1,963.55	0%	0%	0%
				5%	687.95	687.95	109.78	$1,615.43	5%	23%	-18%
				10%	720.71	720.71	117.18	$1,521.45	10%	31%	-23%

				15%	753.47	737.01	120.00	$1,489.03	12%	34%	-24%
				20%	786.22	737.01	120.00	$1,489.03	12%	34%	-24%
Base Case	**654.96**	**88.51**	**$1,963.00**	0%	654.96	654.96	88.51	$1,963.00	0%	0%	0%
				5%	687.71	687.71	108.86	$1,614.97	5%	23%	-18%
				10%	720.46	720.46	116.28	$1,521.03	10%	31%	-23%
				15%	753.21	742.43	120.00	$1,478.67	13%	36%	-25%
				20%	785.96	742.43	120.00	$1,478.67	13%	36%	-25%
10% Increase	**654.79**	**87.74**	**$1,962.57**	0%	654.79	654.98	89.00	$1,952.48	0%	1%	-1%
				5%	687.53	687.53	108.13	$1,614.61	5%	23%	-18%
				10%	720.27	720.27	115.55	$1,520.70	10%	32%	-23%
				15%	753.01	746.97	120.00	$1,470.45	14%	37%	-25%
				20%	785.75	746.97	120.00	$1,470.45	14%	37%	-25%
20% Increase	**654.66**	**87.10**	**$1,962.23**	0%	654.66	654.66	87.10	$1,962.23	0%	0%	0%
				5%	687.39	687.39	107.52	$1,614.33	5%	23%	-18%
				10%	720.12	720.12	114.96	$1,520.44	10%	32%	-23%

				15%	752.85	750.84	120.00	$1,463.78	15%	38%	-25%
				20%	785.59	750.84	120.00	$1,463.78	15%	38%	-25%

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