Shifting last mile delivery operations to Road Autonomous Delivery Robots: Effects on residential streets

WORKING PAPER

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Abstract

We present an analysis of the impacts of last-mile delivery vehicles on pavement lifespans in residential streets. We argue that an increase in the number of parcels delivered daily could be a possible cause for increases in pavement maintenance expenditures in small cities and residential areas. This externality is often overlooked in the current literature. The adoption of RADRs has the potential to help reduce the negative impacts of last-mile delivery on pavement lifespans, since RADRs can be much lighter than conventional delivery vans. We propose the provision of subsidies for the construction of micro-depots as a financial tool that city officials can use to incentivize a faster shift away from conventional delivery vans, instead of spending additional public funds on tighter maintenance schedules or thicker pavement surfaces. We present our calculations as a case study for the city of Evanston, comparing two solutions for a last-mile delivery scenario where 3,000 packages are to be delivered daily: a central depot with conventional delivery vans, and a set of micro-depots scattered throughout the city where RADRs replace the conventional vans and their human drivers. Results indicate that, in the current situation, private delivery firms would need to be provided with external financial incentives to adopt RADRs as their main technology solution. However, as the prices of RADRs go down and the number of parcels to be delivered go up, RADRs are likely to become a more viable option.

1 Introduction

Connected Autonomous Vehicles (CAVs), advanced fuel propulsion systems, e.g., battery-electric vehicles, and other advances, are likely to have profound effects on the way transportation infrastructure is used and, therefore, on the tens of billions of dollars that are invested each year both on capital projects and on preservation of roads, bridges, and other facilities in the United States (and elsewhere). Accounting for and responding to fundamental changes in the use of transportation infrastructure motivates the need both to re-optimize the timing, location, and scope of interventions/investments aimed at improving infrastructure condition, as well as to reconsider the design and operation of transportation systems, e.g., parcel delivery operations in residential areas.

The scope of evaluation of investments in design, construction, management and operations of transportation infrastructure typically involves a detailed accounting of direct costs incurred by owners/agencies/operators. This assessment approach, therefore, fails to capture significant indirect economic impact of investments, as well as direct and indirect social and environmental repercussions. Similarly, approaches to evaluate (firms') investments in re-designing transportation services or in technology adoption, e.g., widespread adoption of CAVs, do not capture their effects on the use and wear of public infrastructure, and thus, on the investments needed to keep these systems operating efficiently, i.e., in a state of good repair, which is required to capitalize on the promise of redesigned/new systems and technologies.

In this study, we focus on a particular indirect impact of the adoption of CAVs for parcel delivery operations in residential areas that, to the best of our knowledge, has been overlooked. Specifically, we quantify the benefits of adoption of Road Autonomous Delivery Robots (RADRs) on reducing the deterioration, i.e., extending the service lives, of street surfaces, i.e., pavements. In particular, because RADRs are significantly lighter than conventional delivery vehicles, they have significant potential to help reduce the negative impacts of last-mile delivery to residential streets – partly, because they are not designed to support the loads induced by delivery vehicles. Importantly, the aforementioned, indirect benefits are linked to the investments needed to deploy and operate the advanced delivery system. We apply the framework developed herein to study widespread adoption of RADRs in Evanston, IL, a small city of approximately 75,000 residents in the Midwestern United States, where pavement maintenance expenditures have recently been increasing due, in part, to growing delivery operations. When comparing two potential scenarios for last-mile delivery (one with conventional delivery vans and another one with RADRs), we find that, in the current situation, private firms would need to be provided with financial incentives to decide to switch to RADRs as their main delivery technology, since this alternative is 65% more expensive. If the prices of RADRs go down and the number of parcels to be delivered go up, RADRs are highly likely to become a viable option. We also find that the current expenditures by the city of Evanston on pavement maintenance would be sufficient to incentivize private firms to make this switch, if these funds were to be allocated for that purpose instead. These findings lead us to believe there is opportunity for the city of Evanston to reconsider its maintenance budget allocation in a more efficient way, by encouraging delivery firms to adopt RADRs and reducing pavement deterioration. These findings were shared with the Director of Public Works in The City, who has expressed interest in the findings presented herein, and importantly, has provided extensive feedback to the research team.

2 Literature review

Delivery demands generated by e-commerce are said to be growing at a double-digit annual rate [Jennings and Figliozzi, 2020]. Pitney Bowles forecasts home delivery volumes will continue to increase, from 20.2 billion parcels delivered in 2020 to 32–39 billion sent out in 2026 [Fagan et al., 2022]. This sharp increase in volumes is predicted to be accompanied by a shift in the technology employed for last-mile delivery, motivated by exacerbated conventional delivery challenges and by a pandemic-mediated need for contactless deliveries [Srinivas et al., 2022].

Among these rising challenges, increasing labor costs seem to be the most notable one. In fact, the shortage of delivery professionals has compelled companies like Amazon to double their pay in an effort to attract and retain workers [Srinivas et al., 2022]. The aging workforce in many industrialized countries only amplifies the problems employers face when hiring the required manpower [Boysen et al., 2021]. Fagan et al. [Fagan et al., 2022] also cite labor as the biggest financial challenge the industry faces when it comes to the last mile of service, which accounts for about half of the total shipping cost. The pandemic has only exacerbated labor shortages, which have been present for years.

Given these trends and challenges, leaders in the industry have come to the conclusion that vehicle autonomy is the way forward for future growth and profitability, and are joining forces to introduce self-driving delivery vehicles in the US [Fagan et al., 2022]. Currently dozens of existing and startup players backed by billions in capital funding are attempting to establish themselves in the area, with both road and sidewalk autonomous delivery robots, as well as drones, as potential solutions [Fagan et al., 2022]. Jennings et al. [Jennings and Figliozzi, 2020] state that robots may soon be delivering parcels to residential customers on the regular, although most deployments are still at the pilot level. According to Srinivas et al. [Srinivas et al., 2022], developments in the adoption of RADRs across various delivery applications have accelerated in recent years, and several companies (such as Amazon, Walmart, and FedEx) are already employing RADRs to perform their delivery operations.

Optimizing fleet and infrastructure decisions is critical for running a profitable logistics business. These decisions are often interlinked, so it is beneficial to study them together [Srinivas et al., 2022]. According to Srinivas et al. [Srinivas et al., 2022], research on RADRs is still in the early stages. Jennings et al. [Jennings and Figliozzi, 2020] also mention a lack of studies focusing on urban deliveries or short-haul freight trips.

It is worth noting the potential societal benefits that the adoption of RADRs may bring along with lower labor costs for companies. While Boysen et al. [Boysen et al., 2021] raise the concern that growing parcel volumes to be delivered toward customer homes will steadily increase the number of delivery vans entering city centers, adding to congestion and pollution, Fagan et al. [Fagan et al., 2022] mention that RADRs offer the potential for reducing this congestion through greater vehicle efficiency by "right-sizing" fleets, trip stacking, and operating for longer hours. Moreover, RADRs can potentially provide safety benefits by reducing crashes and accidents resulting from human error. Hossain [Hossain, 2022] points out robots can potentially reduce the traffic congestion and parking problems and reduce last-mile delivery costs down by 40%.

We note that there is no mention in the literature, as far as we are aware of, of the positive effects RADRs could potentially have on pavement maintenance. Skiles et al. [Skiles et al., 2025] predict that an increase in the number of delivery vehicles in residential areas across the country will lead to quicker wear on the road surfaces. To deal with this issue, the authors propose an increase in pavement surface thickness, assuming the maintenance schedule is to remain unchanged. In our study, we propose an alternative solution to this problem: allowing heavy vehicles only on certain streets, and using RADRs on all other streets. With RADRs being lighter than conventional delivery vans (and even lighter than personal vehicles), this would constitute a potential benefit that remains to be explored.

3 Background

Geographic data for the city of Evanston is available through the city's open data portal. Moreover, population data is available through the 2020 Census Demographic Data Map Viewer. Figure 1 shows the population density for the city of Evanston.

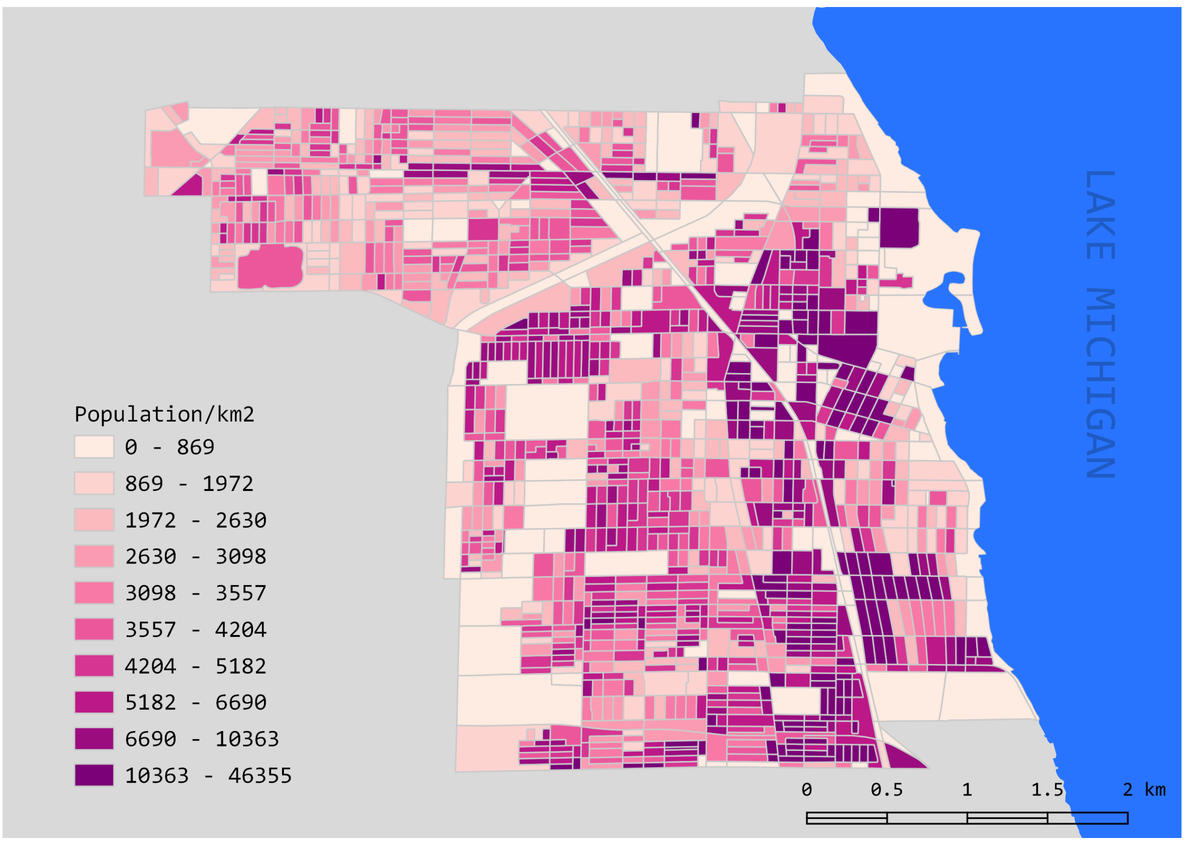


Figure 1: City of Evanston population density by census block

We identify the geometric centroid for each of the 18 census tracts that correspond to the city of Evanston. In our facility location model, these 18 nodes will constitute both demand nodes and potential locations for micro-depots where the RADRs will be loaded and deployed. Figure 2 presents the 18 nodes.

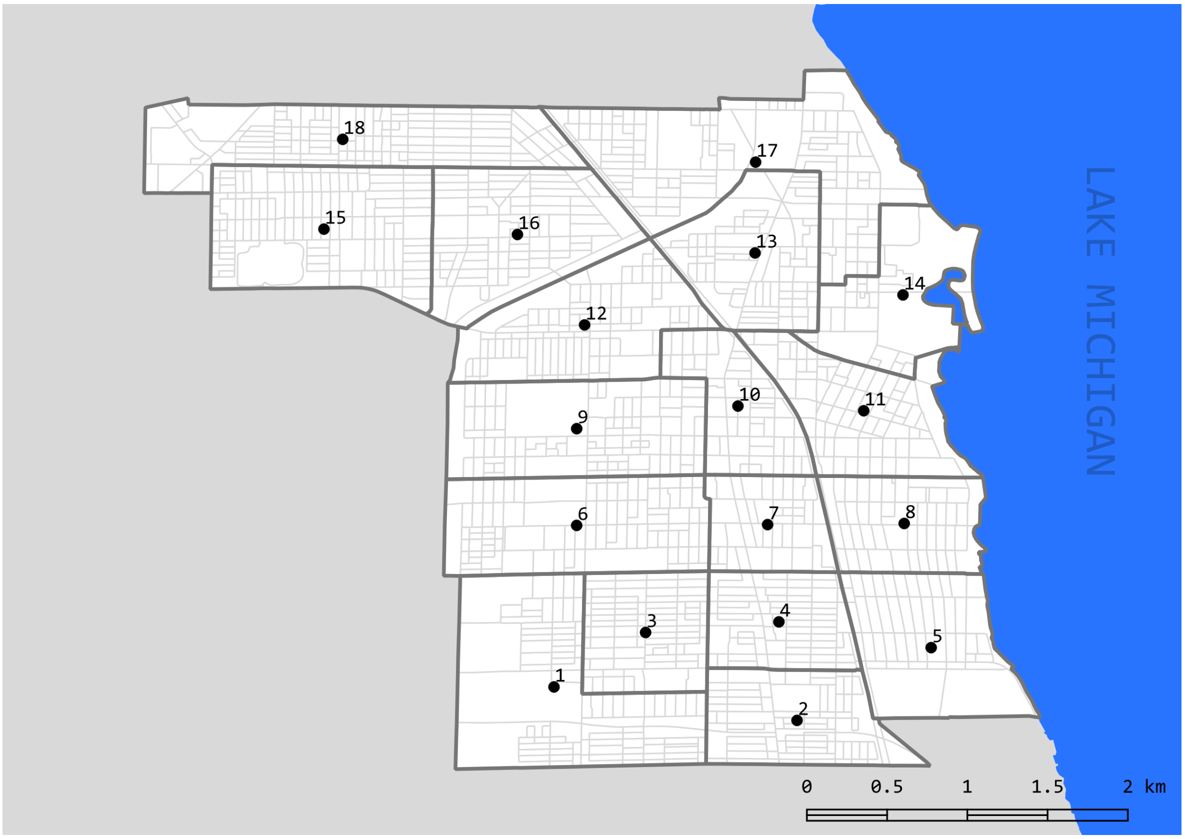


Figure 2: Census tracts with geometric centroids

4 Methodology

As in Boysen et al. [Boysen et al., 2021], we envision for the basis of our case study a delivery concept based on delivery vehicles departing from one major central depot, each driven by a human worker. On a tour along customer homes, the worker stops the vehicle at the roadside, approaches a customer home, and hands over a parcel directly to the customer.

We compare this standard approach to delivery with a second system that involves the use of RADRs. In this second approach, micro-depots are located throughout the city, and fleets of RADRs are available at each micro-depot. The RADRs are loaded and deployed to customer homes, where the customers need to go outside and pick up their parcels. Fagan et al. [Fagan et al., 2022] bring up the fact that consumers being willing to accept curb delivery is still an open question.

Our goal is to formulate a framework that captures direct and indirect impacts of infrastructure investments to support deployment and operation of RADRs. We put our focus in particular on pavement maintenance as a significant indirect impact.

4.1 Distance and time formulations

We take the formulation for distance traveled by a delivery vehicle and time duration of a shift from Jennings et al. [Jennings and Figliozzi, 2020]. According to the authors, the average distance traveled by a delivery vehicle to serve n customers $l(n)$ can be estimated as follows:

$$l(n) = 2d + k_l\sqrt{an}$$

where d represents the distance between the service zone and the depot, k_l corresponds to a routing constant representing non-Euclidean travel on roads, and a represents the area of the service zone. Moreover, the formula that Jennings et al. [Jennings and Figliozzi, 2020] use to calculate route duration time to serve n customers $\tau(n)$ (accounting only for driving time, not taking into account the time of waiting for the customer and unloading the parcels) is as follows:

$$\tau(n) = \frac{2d}{s_h} + \frac{k_l\sqrt{an}}{s}$$

where s_h represents the average speed of a vehicle while traveling to and from the service zone, and s represents the average speed of a vehicle while delivering in the service zone.

4.2 Facility location model adapted for deployment of RADRs

The analysis of the use of RADRs for delivery requires the formulation of a facility location model to understand where the micro-depots should be opened and to estimate the size of the fleet required at each of them. We follow Daskin [Daskin, 2013] to formulate a capacitated fixed charge facility location model and we adapt it to our particular situation.

Instead of a decision variable Y_{ij} indicating the fraction of demand from node $i \in I$ that is satisfied by a micro-depot $j \in J$, we propose a decision variable V_{ij} indicating the number of RADR trips that depart micro-depot $j \in J$ to cover demand at node $i \in I$. Just like in Daskin [Daskin, 2013], we use the problem constraints to ensure all demand is covered, that a micro-depot has to be open in order to be able to satisfy demand, and that micro-depot capacity is not exceeded at any location. Moreover, we add another decision variable to the model: Z_j, indicating the number of RADRs available at site $j \in J$. We also add an additional constraint to ensure a sufficient number of RADRs are available to cover all trips departing a certain micro-depot.

4.2.1 Decision Variables

- $X_j = \begin{cases} 1 & \text{if locating a micro-depot at candidate site } j \in J \\ 0 & \text{otherwise} \end{cases}$
- Z_j = number of RADRs available at site $j \in J$
- V_{ij} = number of trips departing site $j \in J$ to cover demand at node $i \in I$

4.2.2 Parameters

- f_j = fixed cost of locating a micro-depot at candidate site $j \in J$
- k_j = processing capacity of facility at candidate site $j \in J$
- h_i = number of RADR trips required to cover demand from node $i \in I$
- a_i = service area represented by demand node $i \in I$

- d_{ij} = distance between demand node $i \in I$ and facility site $j \in J$
- k_l = routing constant representing non-Euclidean travel on roads
- q = number of parcels carried by a RADR
- s_h = average speed of a RADR while traveling to and from the service area
- s = average speed of a RADR while delivering in the service area
- c = cost per hour of operation of a RADR
- p = cost of purchasing a RADR
- t = time a RADR is idle during a delivery
- g = available hours in a workday
- M = arbitrarily large constant, used for constraint definition

4.2.3 Objective Function

The objective is to minimize the total expenditures, which consist of the capital expenditure of opening the micro-depots, the capital expenditure of purchasing the RADRs, and the operational expenditures of delivery.

$$\text{minimize} \quad \sum_{j \in J} f_j X_j + p \sum_{j \in J} Z_j + c \sum_{i \in I} \sum_{j \in J} V_{ij} \tau_{ij}$$

where $\tau_{ij} = \frac{2d_{ij}}{s_h} + \frac{k_l \sqrt{a_i q}}{s}$.

4.2.4 Constraints

$$\sum_{j \in J} V_{ij} \geq h_i \quad \forall i \in I \tag{1}$$

$$V_{ij} \leq M X_j \quad \forall i \in I, \forall j \in J \tag{2}$$

$$q \sum_{i \in I} V_{ij} \leq k_j X_j \quad \forall j \in J \tag{3}$$

$$\sum_{i \in I} V_{ij} \left(\tau_{ij} + tq \right) \leq g Z_j \quad \forall j \in J \tag{4}$$

$$X_j \in \{0, 1\} \quad \forall j \in J \tag{5}$$

$$Z_j \in \mathbb{N} \quad \forall j \in J \tag{6}$$

$$V_{ij} \in \mathbb{N} \quad \forall i \in I, \forall j \in J \tag{7}$$

- Constraint (1) ensures that demand is satisfied at each each node $i \in I$.
- Constraint (2) ensures that a shift can only depart from a site $j \in J$ if a micro-depot is open at that site.
- Constraint (3) ensures that the capacity k_j of a micro-depot $j \in J$ is not exceeded.

- Constraint (4) ensures that the RADRs available at micro-depot $j \in J$ are sufficient to cover the shifts departing from that micro-depot.

Additionally, we can check off-line for the maximum distance traveled by a RADR not to exceed a range limit r.

4.3 Model data

4.3.1 Location parameters

The population data for each census tract was used directly to estimate demand at each node, by assuming each person receives a total of 14 packages each year [Capital One Shopping, 2024]. Multiplying population by 14 and dividing by 365 gave us the number of packages demanded daily at each node. The total number of packages for the entire city of Evanston would be approximately 3,000 per day. This is further explored in the sensitivity analysis.

Euclidean distances between the nodes were measured in order to create the distance matrix. The land area covered by each census tract was associated to each corresponding node.

Moreover, we created a budget for the distribution facilities, where the fixed costs come from land costs and construction costs. For land cost data, we used sale prices for available land plots on Zillow to estimate an average cost per square foot for the city of Evanston, which led to a value of \$56/sqft. For construction costs, we assumed an average cost of \$18/sqft [APX Construction Group, 2024]. Finally, according to Pahwa et al. [Pahwa and Jaller, 2022], we assumed 0.2 orders can be fulfilled per each square foot of facility.

4.3.2 Vehicle parameters

According to Jennings et al. [Jennings and Figliozzi, 2020], three companies are currently developing RADRs in the US: Nuro (based in Mountain View, California), Udelv (based in Burlingame, California) and AutoX (based in San Jose, California). Nuro's R2 delivery robot, which we have selected for the study, has two compartments with doors that swing upwards to release delivery items. Figure 3 presents the vehicles selected for the study.

Table 1 presents the corresponding parameters for each type of delivery vehicle. The routing constant k_l is taken from Jennings et al. [Jennings and Figliozzi, 2020]. We assume no restriction for the range r of a conventional van, and the restriction for the range r of a RADR is taken from Jennings et al. [Jennings and Figliozzi, 2020]. The capacity q of a conventional van is taken from Jennings et al. [Jennings and Figliozzi, 2020], and the capacity q of a RADR is taken from Ferguson [Ferguson, 2020]. The cost c_{drive} per hour of operation of a van while driving is taken from Jennings et al. [Jennings and Figliozzi, 2020], and c_{drive} for a RADR is assumed to be the same as the one for a van minus the labor cost of the delivery driver. The cost c_{idle} per hour of operation of a van while idle is assumed to come only from the labor cost of the delivery driver, and it is set at \$20/hr. We assume no cost per hour of operation for a RADR being idle, since there is no human driver. The average speed s_h of a van while traveling to and from a service area is taken from Jennings et al. [Jennings and Figliozzi, 2020], and the s_h for a RADR

(a) Ford Transit 2024 cargo van

(b) Nuro R2 delivery robot

Figure 3: Conventional van and RADR selected for the study

is assumed to be the maximum speed taken from Ferguson [Ferguson, 2020]. The average speed s of a van while delivering in a service area is taken from Jennings et al. [Jennings and Figliozzi, 2020], and the one for RADRs is assumed to be the same. The time t a van is idle during a delivery is assumed to be 0.5 minutes, and a longer t of 1 minute is assumed for RADRs since no human driver is present to speed up delivery (this is further explored in the sensitivity analysis). The cost p of purchasing a van is based on a \$50,000 price taken from Ford and assuming a 10 year lifespan and a 6% interest rate. The cost p of purchasing a RADR is also based on a \$50,000 price and the same assumptions of lifespan and interest rate as for vans; however, since the price of a RADR is not publicly available and it is expected to change significantly in the near future [Lee et al., 2016], the implications of this parameter also need to be explored further in the sensitivity analysis.

Symbol	Van	RADR	Units	Explanation
k_l	0.7	0.7	-	routing constant representing non-Euclidean travel on roads
r	-	3	km	range of a vehicle
q	200	2	parcels	capacity of a vehicle
c_{drive}	40	20	\$/hr	cost per hour of operation of a vehicle while driving
c_{idle}	20	0	\$/hr	cost per hour of operation of a vehicle while idle
s_h	70	40	km/hr	average speed of a vehicle while traveling to and from the service area
s	35	35	km/hr	average speed of a vehicle while delivering in the service area
t	0.5	1	min	total time a vehicle is idle during a delivery
p	20	20	\$/day	cost of purchasing a vehicle
g	8	8	hr	available hours in a workday

Table 1: Characteristics of delivery vehicles

5 Analysis and results

5.1 Conventional vans

For the case of conventional vans, we assume one central distribution facility that covers the entire city of Evanston (an area of about 20.15 km^2). Since there are approximately

3,000 parcels to be delivered within a day, and we are assuming each van can carry about 200 parcels, we estimate a total of 15 shifts needed per day. We calculate the driving time of a van per shift and the idle time of a van per shift as follows:

$$\text{Driving time} = \frac{k_l\sqrt{aq}}{s} = 1.5 \text{ hr}$$

$$\text{Idle time} = qt = 1.7 \text{ hr}$$

Adding these times and considering an 8 hour shift, we estimate a total of 8 vehicles that need to be available at the facility to cover the 15 shifts. Assuming a 6% interest rate and a 10-year lifespan, we calculate the daily cost of a central facility to serve the 3,000 daily orders, which would require a 15,000 sqft area, to be approximately $410 per day. Considering a $20 daily cost of purchasing a vehicle, the 8 vehicles would add up to a cost of $160 per day. Finally, the operational expenditures, given the number of shifts and the driving and idle times, would add up to approximately $1,260 per day. The total cost of the conventional vans configuration for the distribution of packages in the city of Evanston would be $1,830 per day. These costs are summarized in Table 2.

Capital expenditures: facilities	410	$/day
Capital expenditures: vehicles	160	$/day
Operational expenditures	1,260	$/day
Total expenditures	1,830	$/day

Table 2: Expenditures for conventional vans solution

5.2 RADRs

The available data for the city of Evanston was used to run the model, considering micro-depots that serve a maximum of 1,000 customers (with a cost of $140 per day and a 20% extra for the two downtown census tracts). The optimal solution consists of 7 open facilities and a total of 18 RADRs needed. Figure 4 presents the location of these open facilities.

Table 3 presents total expenditures for this solution.

Capital expenditures: facilities	1,010	$/day
Capital expenditures: vehicles	360	$/day
Operational expenditures	1,640	$/day
Total expenditures	3,010	$/day

Table 3: Expenditures for RADRs solution

6 Sensitivity analysis

6.1 Effect of capacity constraint and RADR range limitation

We run the facility location model without the micro-depot capacity constraint and without a limitation in RADR range, and we subsequently add back these restrictions

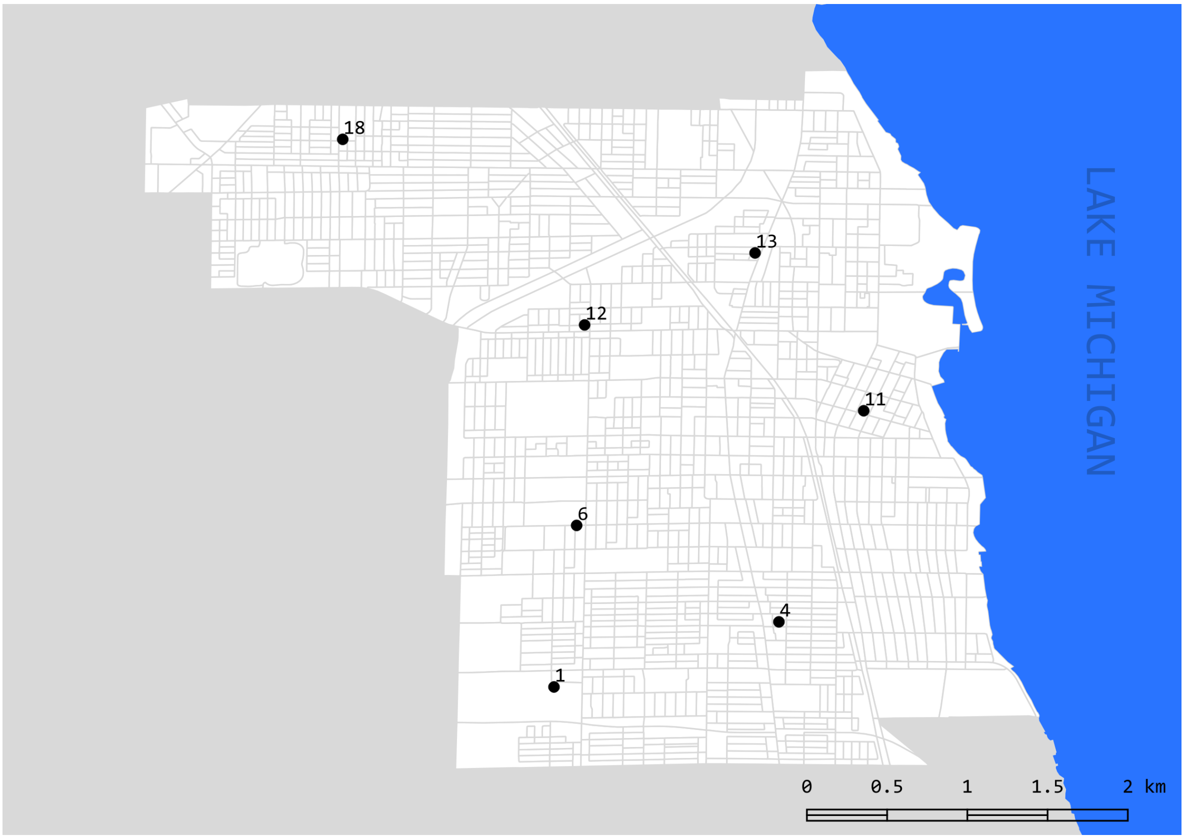


Figure 4: Nodes with open micro-depots

to see what effect they have (if any) on the solution. The results are summarized in Table 4.

Micro-depot capacity constraint				✓
Check for RADR range				✓
Number of open facilities	6	6	7	7
Number of RADRs	18	18	18	18
Capital expenditures: facilities ($/day)	870	870	1,010	1,010
Capital expenditures: vehicles ($/day)	360	360	360	360
Operational expenditures ($/day)	1,718	1,718	1,640	1,640
Total expenditures ($/day)	2,948	2,948	3,010	3,010

Table 4: Effect of capacity constraint and RADR range limitation

We can see from Table 4 that the micro-depot capacity constraint is not binding for the base case, and therefore it does not affect this solution. Checking for RADR range to be below r does affect the solution, but the overall cost does not differ significantly (it increases only by 2%).

6.2 Effect of number of parcels to deliver

We analyze the effect that the number of parcels to deliver can have on the base results. Table 5 presents the effects of varying demand on total expenditures for both conventional vans and RADRs.

Demand multiplier	Total expenditures ($/day)		Total expenditures per delivery ($/parcel)	
	Conventional vans	RADRs	Conventional vans	RADRs
0.5	920	2,037	0.61	1.36
1	1,830	3,010	0.61	1.00
1.5	2,730	3,930	0.61	0.87
2	3,640	4,741	0.61	0.79

Table 5: Effect of number of parcels to deliver

While the cost per delivery remains constant for the conventional vans solution regardless of demand, the RADRs solution exhibits economies of scale. This is promising as demand for package deliveries is only expected to increase in the future.

6.3 Effect of idle times

We also analyze the effect of varying vehicle idle times in the solution. Table 6 presents these results.

	Total expenditures ($/day)	
Idle time t (min)	Conventional vans	RADRs
0.5	1,830	2,949
1	2,469	3,010
1.5	2,969	3,081
2	3,468	3,146

Table 6: Effect of idle times

6.4 Effect of RADR cost

As mentioned, the price of a RADR is not publicly available and it is expected to change significantly in the near future. For the base case, we had assumed a price of $50,000. Considering a 10 year lifespan and a 6% interest rate, this came out to $20 per day. We will now also consider prices of $5,000, $10,000, $15,000, $25,000, $75,000 and $100,000 (which, under the same assumptions, come out to $2, $4, $6, $10, $30 and $40 per day, respectively). Table 7 presents the results of this analysis.

RADR cost p ($/day)	2	4	6	10	20	30	40
Number of open facilities	7	7	7	7	7	7	8
Number of RADRs	19	19	18	18	18	18	17
Capital expenditures: facilities ($/day)	1,010	1,010	1,010	1,010	1,010	1,010	1,150
Capital expenditures: vehicles ($/day)	38	76	108	180	360	540	680
Operational expenditures ($/day)	1,636	1,636	1,640	1,640	1,640	1,640	1,539
Total expenditures ($/day)	2,684	2,722	2,758	2,830	3,010	3,190	3,369

Table 7: Effect of RADR cost

7 Pavement maintenance

[Skiles et al., 2025] study the effects of increases in traffic of delivery vehicles on road wear in the City of Evanston, IL. To understand the cost impact of the increase on pavement patching, the budget for the 2021 and the estimate for the 2022 patching programs are presented in Table 8. The authors note that the number of locations where pavement patching was completed has nearly doubled over the past five years: in 2018, there were a total of 152 patching locations, and in 2022, there were 296 patching locations. Patching extends the life of the road surface by approximately 5 years. A decrease in overall traffic, among other factors, suggests that the observed acceleration of residential street deterioration in Evanston could be explained by an increase in the number of delivery vehicles serving the City of Evanston.

Year	Patching locations	Pavement patching (yd^2)	Total cost (2020 $)
2021	219	31,118	562,000
2022	296	37,500	642,000

Table 8: 2021 and 2022 city of Evanston Pavement Patching Program data

[Skiles et al., 2025] assume a traffic mix where 5% of traffic corresponds to delivery vehicles (14,000 lb), 5% to heavy vehicles (18,000 lb), and 90% to personal vehicles (assumed to be evenly split between an average 4,000 lb car and an average 8,000 lb SUV/pickup truck). They consider a daily traffic of 200 vehicles per day for the average Evanston residential street. The authors use the AASHO equation to find the number of equivalent single axle loads that cause pavement quality to decline to the point where resurfacing is required, N:

$$N = A_0 * (D + 1)^{A_1} * (L_1 + L_2)^{-A_2} * (L_2)^{A_3} \tag{1}$$

where D represents pavement thickness, L_1 and L_2 are parameters determined by the weight and whether the axle is single or tandem, and A_0, A_1, A_2 and A_3 are coefficients that vary slightly depending on whether the pavement is rigid or flexible. L_1 is fixed at 18 and L_2 is fixed at 1 for the study. The authors use two different sets of coefficients A_0, A_1, A_2 and A_3, which are presented in Table 9.

Model	$ln(A_0)$	A_1	A_2	A_3
AASHO	13.65	9.36	4.79	4.33
Small-Winston	12.062	7.761	3.652	3.238

Table 9: Flexible pavement coefficient estimates for AASHO road wear equation [Small et al., 1989]

Both sets of coefficients show that an increase in the number of delivery vehicles causes a significant decrease in pavement lifespan. The authors also consider the effects of replacing conventional delivery vehicles with electric delivery vehicles, which they assume to be 1,444 lb heavier. Their results are summarized in Tables 10 and 11, for a two-fold and four-fold increase in the number of delivery vehicles.

Model	Years to pavement failure		
	1X delivery veh.	2X delivery veh.	4X delivery veh.
AASHO	11.15	9.19	6.80
Small-Winston	9.01	7.43	5.50

Table 10: Pavement performance with conventional delivery vehicles, based on [Skiles et al., 2025]

Model	Years to pavement failure		
	1X delivery veh.	2X delivery veh.	4X delivery veh.
AASHO	9.99	7.72	5.30
Small-Winston	8.08	6.24	4.29

Table 11: Pavement performance with electric delivery vehicles, based on [Skiles et al., 2025]

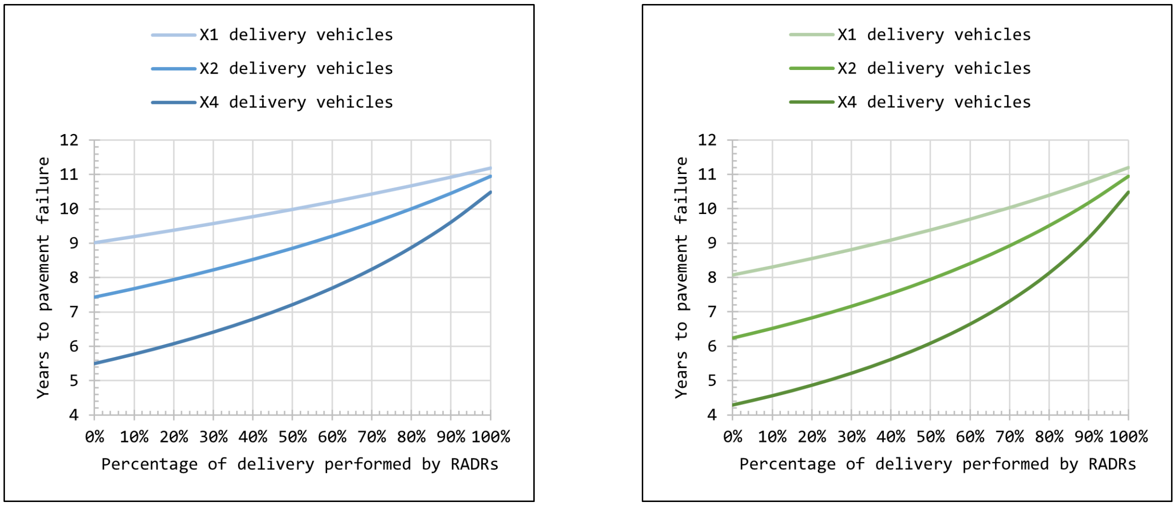
As an approach to mitigate the service life reduction from the increased traffic loads associated with delivery vehicles, [Skiles et al., 2025] discuss increasing the surface thickness of the pavement.

In this study, we explore an alternative solution. Given that a Nuro RADR has a gross vehicle weight of 1,150 kg and can carry a payload of up to 190 kg [Ferguson, 2020], putting it below the weight of an average car [Skiles et al., 2025], encouraging firms to make use of RADRs instead of conventional delivery vans could potentially help mitigate the impact of last-mile delivery on pavement maintenance. Figure 5 presents our results graphically, where we gradually replace a portion of the total number of delivery vehicles considered by [Skiles et al., 2025] by RADRs. We select a conservative load equivalency factor of 0.0003 for RADRs [Pavement Tools Consortium, 2024], and we assume 100 RADRs for every conventional delivery van (consistent with our selection of q of 200 parcels for conventional vans and 2 parcels for RADRs in the facility location model formulation). Although RADRs are meant to circulate on surface streets, as opposed to SADRs (Sidewalk Autonomous Delivery Robots), their impact in pavement lifespans is minimal, due to their low weight. Therefore, major increases in delivery demands would have relatively minor impacts in pavement lifespans if the adoption of RADRs was 100%.

To put things into perspective, Table 12 presents the increases in pavement surface thickness that would be required to achieve similar pavement lifespans as those resulting from a 100% RADR adoption, under varying assumptions.

Type	Increase in surface thickness (in)		
	1X delivery veh.	2X delivery veh.	4X delivery veh.
Conventional delivery vehicles	0.25	0.40	0.70
Electric delivery vehicles	0.35	0.60	0.95

Table 12: Surface thickness increases to achieve results equivalent to a 100% RADR adoption



(a) Considering conventional delivery vehicles

(b) Considering electric delivery vehicles

Figure 5: Pavement performance versus adoption of RADRs, Small-Winston coefficients

8 Subsidies for micro-depots

Although the results we presented show that the tendency in the near future will be for the total costs a RADR based approach to last-mile delivery to tend towards those of a conventional van based approach (when the number of parcels to deliver increases and the cost of CAVs decreases), the current situation still favors conventional vans. However, we can use our model to attempt to understand what would be the case if the government were to provide subsidies for the use of RADRs. In particular, we look at the results when the government decides to cover part of the cost of the micro-depots. These results are summarized in Table 13.

Subsidy (% of total facility costs)	0%	25%	50%	75%	100%
Number of open micro-depots	7	8	11	17	18
Number of RADRs	18	17	16	17	18
Capital expenditures: facilities ($/day)	1,010	862	785	610	0
Capital expenditures: vehicles ($/day)	360	340	320	340	360
Operational expenditures ($/day)	1,640	1,539	1,278	932	888
Total expenditures ($/day)	3,010	2,741	2,383	1,882	1,248
Subsidy ($/day)	0	287	785	1,830	2,580

Table 13: Effect of government subsidies

We can see from these results that higher subsidies encourage private firms to open more micro-depots. Moreover, subsidies in the 75-100% range would bring total costs for private firms around the same level as those of conventional vans. A 75% subsidy would add up to a cost of around $670,000 for the government, which is in the same order of magnitude as the cost of the pavement patching program presented on Table 8. This leads us to believe that providing subsidies for the construction of micro-depots could potentially be a viable way to mitigate the social costs of an increase in delivery vehicles, as an alternative to the increase in pavement thickness proposed by [Skiles et al., 2025]

9 Conclusion

We study a benefit of the use of RADRs which is often overlooked when considering the possible repercussions of adoption of CAVs: using lighter delivery vehicles on residential streets would decrease the need for regular pavement maintenance. An increase in delivery demands generated by e-commerce can have a significant negative impact in pavement lifespans in residential areas, and the use of heavier electric delivery vans only exacerbates this problem. For instance, a four-fold increase in the number of delivery vehicles could make pavement lifespans up to four years shorter than they currently are. However, the gradual adoption of RADRs has the potential to offset the effects of this externality.

For our analysis, we developed a case study for the city of Evanston, where we compared two potential solutions for a last-mile delivery scenario where around 3,000 packages need to be delivered daily. On one hand, we considered a central depot where conventional delivery vans are deployed. On the other hand, we considered a set of micro-depots scattered throughout the city, where RADRs replaced the conventional vans and their human drivers. Solving this second alternative required us to formulate a facility location model.

Our results suggest that private delivery firms would need to be provided with financial incentives to shift to using RADRs as their main delivery vehicles, given the current situation. As the prices of RADRs go down and the number of parcels to be delivered go up (like they are both predicted to), RADRs are likely to become a much more viable option than they are today. In the meantime, our proposal to the city of Evanston is that they could allocate part of their yearly pavement maintenance budget to providing financial incentives to private delivery firms for the use of RADRs, thus reducing the overall amount of heavy delivery vans circulating and with it the rate at which surface roads deteriorate.

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Code for facility location model

The Matlab code corresponding to the adapted facility location model follows.

```
% Parameters
q = 2;

% Matrices
f = readmatrix('fixedCost.csv');
k = readmatrix('capacity.csv');
h = ceil(readmatrix('demand.csv')/q);
a = readmatrix('serviceArea.csv');
d = readmatrix('distance.csv');

% Constants
kl = 0.7;
r = 3;
cd = 20;
ci = 0;
sh = 40;
s = 35;
t = 1/60;
T = 8;
p = 20;
g = 8;
M = 1000;

% Decision variables
X = optimvar('X',length(f),'Type','integer','LowerBound',0,'UpperBound',1);
Z = optimvar('Z',length(f),'Type','integer','LowerBound',0);
V = optimvar('V',length(h),length(f),'Type','integer','LowerBound',0);

% Objective function

% Vehicle operation times
for i = 1:length(h)
    for j = 1:length(f)
        opTimeDrive(i,j) = V(i,j)*(2*d(i,j)/sh + (kl/s)*sqrt(a(i)*q));
        opTimeIdle(i,j) = V(i,j)*(t*q);
    end
end

% Capital expenditure
capExF = sum(f(:).*X);
capExV = sum(Z)*p;

% Operational expenditure
```

```
opExV = sum(sum(opTimeDrive))*cd + sum(sum(opTimeIdle))*ci;

% Total expenditure
totalEx = capExF + capExV + opExV;
prob = optimproblem('Objective',totalEx,'ObjectiveSense','min');

% Constraints
demand = optimconstr(length(h));
for i = 1:length(h)
    % demand(i) = q*sum(V(i,:)) >= h(i);
    demand(i) = sum(V(i,:)) >= h(i);
end

assign = optimconstr(length(h),length(f));
for i = 1:length(h)
    for j = 1:length(f)
        assign(i,j) = V(i,j) <= M*X(j);
    end
end

capacity = optimconstr(length(f));
for j = 1:length(f)
    capacity(j) = q*sum(V(:,j)) <= k(j)*X(j);
end

range = optimconstr(length(h),length(f));
for i = 1:length(h)
    for j = 1:length(f)
        range(i,j) = V(i,j)*(kl*sqrt(a(i)*q) + 2*d(i,j)) <= V(i,j)*r;
    end
end

vehicle = optimconstr(length(f));
for j = 1:length(f)
    vehicle(j) = Z(j) >= (sum(opTimeDrive(:,j))+sum(opTimeIdle(:,j)))/g;
end

prob.Constraints.demand = demand;
prob.Constraints.assign = assign;
prob.Constraints.capaci = capacity;
prob.Constraints.range = range;
prob.Constraints.vehicle = vehicle;

% Solver
sol = solve(prob);
```