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A Two-Tier Urban Delivery Network with Robot-based Deliveries

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Abstract

In this paper, we investigate a two-tier delivery network with robots operating on the second tier. We determine the optimal number of local robot hubs as well as the optimal number of robots to service all customers and compare the resulting operational cost to conventional truck-based deliveries. Based on the well-known p-median problem, we present mixed-integer programs that consider the limited range of robots due to battery size. Compared to conventional truck-based deliveries, robot-based deliveries can save about 70% of operational cost and even more, up to 90%, for a scenario with customer time windows.

1 Introduction

"In the final-mile world, there's more work than you can handle," says Leonard Wright of INPAX Shipping Solutions, a courier service that makes deliveries for clients such as Amazon (Sasso, 2018). The growth in e-commerce has created a huge increase in demand for drivers to travel the last mile to the customer. This is reflected in the tripling of job postings for delivery drivers in the U.S. on Indeed.com since 2016 (Sasso, 2018). Given the growth in e-commerce and the accompanying shortage of drivers, many companies around the world are developing their own visions for the use of autonomous vehicles to help with the challenges of last-mile deliveries. Examples include Amazon's use of drones to deliver packages, Google and DHL's plans to build driverless delivery vehicles, DHL's proposed self-driving parcels, and the US Postal Service's ideas for self-driving mail trucks (Marshall (2017); DHL (2014)).

One of the most popular autonomous delivery concepts involves the use of unmanned aerial drones. Drones are capable of carrying loads of cargo over a limited distance. Drones are naturally less constrained in terms of movement than delivery vehicles, since they are flying and are thus not subject to crowded traffic infrastructure. However, drone usage might become quite limited. A NASA study has found that drone noise is more annoying to people than noise emissions by cars (Christian and Cabell (2017)). In addition, the US Federal Aviation Administration requires drone operators to keep the unmanned aircraft within eye shot at all times, and a drone operator cannot be responsible for more than one unmanned aircraft at a time (FAA (2018)). Drones are also often not allowed in the vicinity of airports. For instance, it is prohibited to use a drone within a 15 mile radius of Ronald Reagan Washington National Airport (FAA (2017)). All of these issues currently limit the potential applications for drone-based deliveries.

Unlike drones, self-driving robots driving on sidewalks to deliver a single or multiple parcels seem to be a promising mode of transportation for last-mile deliveries in the same types of locations where drones may be restricted. Public opinion about these robots is generally very positive. A USPS survey says that three out of four people would accept robot deliveries, and around 30% would be willing to pay slightly more for robot delivery if the use of a robot means that the package can be delivered when and where the recipient chooses (USPS (2018)).

Several companies are either already selling or developing delivery robots. Starship Technologies is currently selling robots that can drive up to six kilometers with a maximum speed of 6 km/h. They can carry up to 10 kg in their 1.61 ft^3 cargo compartments (StarshipTechnologies (2015)). Other companies like Marble, Robby, FedEx and Amazon are also developing their own robots (Scott (2019)). For instance, Robby's robots can go as fast as 10 km/h and can cover 35 kilometers with one battery charge (Robby (2018)). With cameras, ultrasonic obstacle detectors and GPS, a robot can potentially operate in a highly autonomous manner with just one person supervising up to 100 of them. Human supervision and control might be needed during challenging situations such as high traffic road crossings or traffic accidents (Sulleyman (2017)). Starship Technologies projects that robots can decrease the cost of the shipment of deliveries by a factor of 15, down to under $1 for most shipments (RoboticsBusinessReview (2018)).

Robot delivery is already in operation in several major cities such as London, San Francisco and Washington, D.C. (Lonsdorf (2017), Teale (2018)). Since July 2016, about

1000 food deliveries for Just Eat were performed in the London greater area (Mirror.Co.Uk (2018)). Robots are currently delivering food at Intuit Mount View campus, CA (Sawers (2018)) and at the George Mason University campus (Sodexo (2019)). PizzaHut in New Zealand, DoorDash in California and Postmates in Washington, D.C. are using robots for fast food deliveries (Olson (2018)). Domino's delivers pizza with robots in a handful of German and Dutch cities (Sawers (2017)). Depending on cargo capacity, robots are not limited to just food delivery. Starship Technologies launched a robot package delivery service in Milton Keynes, UK (BBC (2018)). For a monthly subscription fee of a US equivalent $10, a customer can get an unlimited number of robot deliveries from a local hub.

Even though robots can be quite helpful in making deliveries, they have several technological limitations. Limited battery capacity, low travel speed, and the necessity of driving on sidewalks are among them. This makes it challenging to understand the best way to use delivery robots in downtowns and suburbs and the possible savings compared to traditional driver/truck-based deliveries, especially when time-window based deliveries come into play, which create significant costs for traditional deliveries. Most of the limited amount of literature on the use of robots for last-mile deliveries focuses on the use of a manned delivery vehicle that drives to different neighborhoods and then deploys a set of robots for making deliveries near the vehicle (examples discussed in detail in Section 2).

In this paper, we intend to explore a different approach where robots are used in combination with local robot hubs, such as used by Starship Technologies in Milton Keynes. We explore the benefits of utilizing robots in a two-tier delivery system. Our approach follows the idea of two-tier delivery systems as presented by Anderluh et al. (2017), for example, who consider conventional trucks operating on the first tier and bikes on the second tier for deliveries in the city of Vienna. In our case, manned vehicles would drop off a large number of packages at second-tier local hubs, and then the packages would be delivered to their final addresses by a set of robots assigned to that hub. The robots make multiple trips per day back and forth from the robot hub. Based on the well-known p-median problem, we develop mathematical models for such a two-tier system that minimize the operating cost of using robots. We explore different delivery options where robots either deliver a package in a predefined customer time window or without the presence of customers.

We use the mathematical models and our experiments to answer the following questions:

- How many robot hubs and robots do we need for this two-tier delivery model?
- What are the cost savings from using robots vs. conventional single-tier driver/truck-based deliveries?
- How do the savings change for downtown vs. suburban deliveries?

- How do the savings change when customer time windows are considered?
- How do the savings change for varying driver costs and different robot technologies?

We provide an overview of related literature in Section 2. We define our problem in Section 3 and present a mixed integer programming (MIP) model for robot-based deliveries with and without time windows. In Section 4, we introduce the parameters we use in our experiments and the design of our data sets. Computational results for above questions are presented in Section 5. In Section 6, we offer our conclusions and discuss directions for future research.

2 Literature Review

In recent years, several new technologies for last-mile deliveries have been introduced. Interested readers may refer to Savelsbergh and Van Woensel (2016), Kovacs and Kot (2016) or Speranza (2018) for discussions of the latest challenges and new ideas. One of the most popular ideas is the use of autonomous delivery vehicles such as drones and robots. Our approach is clearly related to existing work with aerial drones and other robot-based delivery models, so we discuss the related literature below. At the same time, our models are based on a variant of the multi-trip vehicle routing problem with and without time windows (MVRP, MVRPTW), the p-median problem, and a two-tier vehicle routing problem. For a review of two-tier vehicle routing problems, see Cattaruzza et al. (2017).

2.1 Robots

The number of papers modeling and optimizing the operations of robot-based deliveries has been quite small so far. Boysen et al. (2018) consider launching autonomous robots ("Starship robots") from a single truck to serve deliveries with time windows. In particular, a truck loads a shipment of parcels and robots at a central depot and moves them to a drop-off point in the city center where robots are released to conduct last-mile deliveries. After delivery, the robots return to the drop-off point. Meanwhile, the truck moves to the next drop-off point until all of them have been served. If the truck runs out of robots, it visits the nearest local drop-off point to pick them up again. To optimize their delivery plan, Boysen et al. (2018) introduce a scheduling heuristic that minimizes the number of late deliveries. As expected, in terms of average lateness, the model with robots and decentralized drop-off points outperforms the one where trucks wait for robots. The comparison with a conventional vehicle routing problem shows an increase in the number of vehicles required to ensure the same number of late customers as the decentralized robot model, particularly when the loading time for the robots is shorter than for the delivery person.

Jennings and Figliozzi (2019) follow a similar idea of releasing robots from a vehicle. They use continuous approximation methods and other formulas to estimate the savings that robots can achieve in terms of total delivery time and number of required robots. This is the first paper which specifically addresses the limitation of these robots to sidewalks in their travel times. In their case study, the authors compare their approach with conventional delivery concepts. With an assumption that a robot can service up to six customers and a vehicle can transport up to eight robots at a time, the authors conclude that robots may be more efficient than standard delivery approaches when the average delivery time per customer is high or when the customer density increases. The approaches by Boysen et al. (2018) and Jennings and Figliozzi (2019) both have the disadvantage that manned vehicles have to transport packages as well as delivery robots, which is more time-consuming for the driver than our approach and requires the development of a new vehicle.

Clausen and Schaudt (2018) consider a concept of utilizing decentralized delivery robots. Given a predefined set of robot hubs and robot assignment to these hubs, the authors focus on minimizing tardiness/earliness of parcel deliveries using a parallel-machine-scheduling problem formulation along with a local search heuristic. Their test instances are based on 50 customers and either 3 or 5 robot hubs, and their model can be solved for up to 25 customers in a run time of approximately 10 minutes.

Poeting et al. (2019) simulate the performance of a robot delivery model. Within the simulation, two problems are considered: a Traveling Salesman Problem with Precedence Constraints (TSPPC) and an Orienteering Problem with Multiple Time Windows (OPMTW). The first problem represents the conventional driver/truck-based delivery model and includes the handling of failed deliveries by leaving them at a local hub until the next day. The latter problem represents a combination of trucks and autonomous robots for parcel deliveries. In this model, only a small percentage of parcels is delivered by robots (0-3%). Once packages to be delivered by robots have been identified, a vehicle delivers those packages to local hubs where robots can then deliver them to customers. The assignment of parcels to local depots is assumed to be given, and each local depot only has one robot. The objective is to maximize the number of local depots visited by a vehicle which, in turn, maximizes the total number of robot-delivered packages. Four experiments with different proportions of parcels delivered by robots are conducted. The results indicate that the tested levels of robot use have no significant impact on total tour length, which reflects operational cost.

One of the most recent papers is the work by Sonneberg et al. (2019). The authors consider a location-routing problem with the use of multi-compartment robots and customer time windows. The robots start and end their tour at a robot hub and can visit multiple customer locations before returning to the robot hub. It is assumed that robots can easily swap their battery to avoid recharging times. The authors present a mixed-integer linear program that decides which robot hubs should be opened with an objective of minimizing total cost of operations. The total costs are based on rental costs of all utilized delivery robots, the personnel costs for preparing the robots, and the variable delivery costs for all tours (based on total distance and transport cost rate). A single “proof of concept” case is solved with three potential station locations, ten demand locations, and four-compartment robots. Computational experiments analyze the impact of changing the number of compartments of delivery robots.

2.2 Drone Routing

Despite the fact that both drones and robots can operate autonomously, several major differences exist in underlying delivery models. In recent years, researchers have investigated several variants of routing problems involving aerial drones. Some versions consider only drones, where others consider drones in combination with delivery vehicles.

An early paper that considers drones only is by Sundar and Rathinam (2014). The authors analyze a single-drone routing problem with the possibility of having several depots to recharge the drone. The authors want to identify the minimum-cost path that reaches all target locations considering the limited battery/range of drones.

Dorling et al. (2017) assume there is one depot where drones can replace their battery and load their cargo. They model deliveries as an MTVRP. Two different objective functions are considered: minimization of total delivery time and minimization of total cost including cost of drones and energy usage. A simulated annealing-based heuristic is proposed and small instances with six to eight delivery locations as well as bigger instances with 125 or 500 locations are considered. The authors demonstrate big savings from allowing drones to make multiple trips in a day.

Combining delivery trucks with drone-based deliveries, a popular research direction builds on the flying sidekick traveling salesman problem (FSTSP). Here, it is assumed that a truck serves as the “mothership” to release and collect drones. While the FSTSP is more flexible than dispatching drones from a central depot, the challenge of the FSTSP is to synchronize the drone with the mothership to serve all customers in the minimum amount of time. Murray and Chu (2015) introduce the FSTSP and the parallel drone scheduling TSP (PDSTSP). The PDSTSP considers the case when vehicles and drones operate independently. They assume that a mothership can release and accept a drone only at customer locations. Furthermore, a drone can leave and come back to the depot independently of the mothership. Testing of their MIP model reveals that a commercial solver like Gurobi might take up to several hours to solve an instance with 10 customers to optimality. Note that this paper does not consider multiple trips for drones, so if multiple customers are served by drones, then there should be the same number of drones as customers.

Agatz et al. (2018) also examine a version of the FSTSP. In particular, the truck carries one drone, which can be released from the truck at a customer location or the depot. The drone can carry one parcel at time. After it has served a customer, it needs to come back to the truck, which waits for the drone at a particular location if necessary. Trucks and drones can serve customers independently and simultaneously. The objective is to minimize the operational cost (total distance) of all operations such that all customers are visited. In the first step of their solution procedure, they solve a classic TSP where no drone nodes are present. In the second step, they add drone nodes using either greedy heuristics or a dynamic programming-based algorithm. To test their model, the authors create three different types of instances: uniform instances, 1-center and 2-center instances. The 1-center instances mimic circular city structures and have more customers closer to the center point. The 2-center instances mimic a city with two centers. It is shown that a combined truck and drone delivery concept outperforms the traditional truck-based delivery. Savings up to 34.1% can be achieved in case of a drone with a speed three times the vehicle speed.

Carlsson and Song (2018) provide a theoretical analysis of the FSTSP. Using their theoretical results, they make predictions about changes in service times when a delivery truck is augmented with a drone. They demonstrate that the improvement in efficiency compared to the truck-only case is proportional to the square root of the ratio of the speeds of the truck and drone. Boysen et al. (2017) consider a special variant of the FSTSP. They assume that the route for the mothership is given and develop a schedule for drones to service a given set of customers. Six variations of this problem with one and multiple drones on a mothership are considered. Computational experiments reveal differences in efficiency of the two presented MIP formulations and demonstrate that one of these can successfully solve large instances with up to 100 customers.

Ulmer and Thomas (2017) analyze the combination of drones with trucks for the same-day delivery problem, in which orders appear dynamically over the course of the day. Drones and trucks operate independently. A drone can deliver only one package at a time. Once a package has been delivered, the drone returns to the depot and recharges. They model this problem as a Markov decision process and present a policy function approximation algorithm that decides whether a customer should be served by a truck or a drone. They show that a combination of drones and trucks may reduce operational costs required to serve the majority of customers in comparison to the truck-only case.

In Wang et al. (2017) and its extension by Poikonen et al. (2017), a multi-truck, multi-drone vehicle routing problem with drones (VRPD) is considered with the goal of minimizing the completion time to deliver all packages and return all vehicles back to a central depot. In their models, demand can be fulfilled either by a truck or a drone. They develop bounds for possible savings when using a mixed fleet of multiple trucks and drones versus using only a homogeneous fleet of conventional delivery trucks. In particular, connections in forms of theoretical objective function bounds and asymptotic results to VRP, VRPD and "close-enough" VRP are provided.

Poikonen and Golden (2018) consider two variants of the FSTSP, or, as the authors call their problem, the mothership and drone routing problem. The main difference between the different variants is the drone capacity. One version assumes that a drone can make only one delivery at a time, the other assumes multiple deliveries. Their models are distinct from the others in this research direction as the mothership vehicle operates in a continuous Euclidean space with the ability to launch and retrieve the drone at any location rather than only at certain nodes. They develop a branch-and-bound method and a greedy heuristic to solve the proposed model. Instances with up 200 customers are considered.

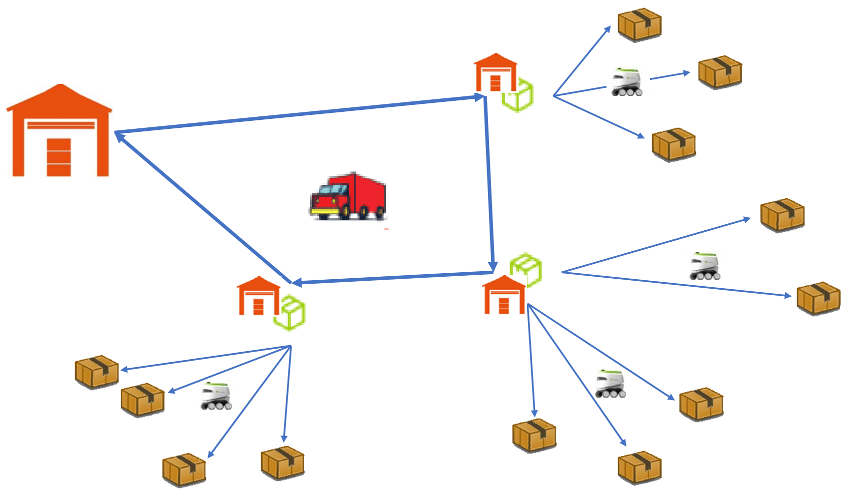
2.3 Multi-trip Vehicle Routing Problems

As robots can make multiple trips in a day from a depot, it is possible to reuse them multiple times over a certain time period. Hence, our problem has features in common with the MTVRP, which are briefly reviewed in the following. However, our problem is simpler in the sense that robots visit customers by pendulum tours between local hubs and customers.

Despite the practical relevance, the amount of literature on the MTVRP is scarce. Cattaruzza et al. (2016) provide a comprehensive review of the MTVRP. Mingozzi et al. (2013) develop two set-partitioning formulations for the MTVRP. They model the problem in two ways. The first model focuses on the creation of all feasible routes. The second one revolves around feasible schedules. The authors study lower bounds of these problems and propose an exact solution approach which can solve instances with up to 120 customers. Azi et al. (2014) develop an adaptive large neighborhood search for the MTVRP. The authors limit the number of available vehicles, so their objective becomes to maximize the number of served customers and then minimize the total distance traveled.

There also papers that take customer time windows into account (MTRVRPTW). Azi et al. (2010) introduce a branch-and-price algorithm for the MTVRPTW. In their case, it is not mandatory to visit all customers. Macedo et al. (2011) develop an exact iterative algorithm based on a pseudo-polynomial network-flow model. Instances with up to 40 customers are investigated and solved to optimality. In Hernandez et al. (2014), a MTVRPTW with trips of limited duration is considered. A two-phase exact algorithm is provided and computational results on Solomon's benchmarks are presented. Instances with up to 40 customers are solved to optimality. Hernandez et al. (2016) consider a similar problem considering a mandatory visit of all customers and no limitations on duration. The authors develop a branch-and-price algorithm that is based on two formulations. Experiments

Figure 1: Structure of Two-Tier City Logistics Network



based on Solomon data sets with up to 25 customers are solved to optimality.

3 Problem Definition and Mathematical Model

In the following, we will define our problem, present mathematical models, and make some observations.

3.1 Problem Definition

Our goal is to explore how autonomous robots could be useful to make parcel deliveries in an urban setting. We try to make our model as realistic as possible. Our two-tier network is depicted in Figure 1. Following the idea of a two-tier urban delivery network as described in Crainic (2008), we assume that a conventional delivery truck travels to every robot hub to fill it with packages (e.g., during the late night or early morning hours, first tier) to be delivered by robots assigned to that particular robot hub (e.g., during the day, second tier). We assume that all robot hubs have a technology to put the right package in each robot.

First, to minimize the need for drivers required to fill the robot hubs, we want to use the fewest number of robot hubs possible to serve our set of customers. This is to address the current driver shortage and understand how a robot delivery model would reduce the need for drivers. Second, using this minimum number of robot hubs, we want to minimize the operational cost of serving the customers with robots. We also want to identify the minimum number of robots at each opened robot hub to achieve this minimum cost of serving customers.

The used notation is summarized in Table 3.1. We will assume that packages can be delivered by robots from local robot hubs chosen from a set of locations $D = \{1, ..., n\}$. We will also assume that the set of potential customer locations $C = \{1, ..., m\}$ is known. We understand that in practice the number and location of customers may vary each day, and hence, we will solve our first-tier models across a large set of instances $\omega \in \Omega$. To enable direct comparisons with conventional deliveries, we set a maximum amount of time M that a robot can be used each day. This can be used in a similar way to restrict the shift lengths for drivers.

Each potential robot hub has a maximum number, r_{max}, of robots it can store. Due to the limited operating time of a robot battery, b, not all customers can be reached from all robot hubs. We assume that robots are limited to one package per delivery. Hence, the robots will perform multiple pendulum tours between robot hubs and individual customers over the course of the day, where the round trip time for delivery from hub location d to customer c requires time $t(d, c)$. Note that $t(d, c)$ is dependent on the speed that the robot travels. Upon each return to the robot hub, robots recharge their battery to full capacity. We assume a robot can be dispatched only if the battery is fully charged, the charge time at the hub is based on the total time of the previous trip, and energy consumption is linear. As a consequence, we can compute the time required for charging based on a simple percentage of the time it would take to fully recharge (t_f). We also consider a service time to load a package into a robot at the hub (t_p) and drop it off at a customer (t_s). We assume that energy consumption during drop off at customers is negligible and hence ignore t_s in the recharge time. The parameter l represents the length of a city block. This reflects the restriction that robots must travel on sidewalks to reach customers. Relatedly, the value for $t(d, c)$ will reflect the Manhattan distance between locations. For simplicity of presentation, we will assume that customers and robot hubs are only located at intersections of these blocks.

3.2 Mathematical Model

The problem we consider is closely related to the p-median problem and the vehicle routing problem. Since delivery robots carry only one package at a time, this allows us to simplify VRP modeling and use only pendulum tours from the hub to the customer and back to the local hub. The p-median or p-center problem, also known as the facility location or network location problem, first appeared in Hakimi (1964) and Hakimi (1965). To the best of our knowledge, our paper is the first one that combines facility location and multi-trip robot deliveries.

Robot parameters	
b	maximum operating time on one battery (hrs)
t_f	full recharge time for a robot (hrs)
M	maximum allowed daily driving time limit for a robot (hrs)
$t(d, c)$	time for a round trip from hub d to customer c and back (hrs) where $c = 1, ...m, d = 1, ...n$
Customer parameters	
C^ω	set of customers in instance $\omega \in \Omega$
e_c	earliest start of service for customer $c = 1 \dots m$ (hrs)
l_c	latest start of service for customer $c = 1 \dots m$ (hrs)
t_s	time to service a customer (hrs)
Other parameters	
n	number of potential robot hub locations
r_{max}	maximum number of robots a robot hub can maintain
l	length of a block (km)
t_p	time per package to put in robot hub

Table 1: Notation

Our first model in Section 3.2.1 addresses the two-tier problem for the case when deliveries have no time windows. This assumes that the robot is capable of leaving a package near a customer's home or entering the customer's home to make a delivery. With the introduction of technologies like "Key by Amazon" (Cosgrove (2019)), customer presence to make a delivery within the home is becoming less of a necessity. However, in case that customers would rather prefer an attended delivery, our second model in Section 3.2.2 reflects the situation when customers pick a time window for their package to be delivered.

3.2.1 No Time Windows

We formulate the no-time-window case as a MIP with the following set of decision variables:

$$x_c^{\omega r d} = \begin{cases} 1 & : \text{if robot} \quad r = 1, ..., r_{max} \text{ from hub } d \text{ serves customer } c, \\ & \quad \text{where } d = 1, ..., n, \ c \in C^\omega, \omega \in \Omega; \\ 0 & : \text{otherwise} \end{cases}$$

The above formulation leads to an explosion in the number of variables, which makes the computation of the optimal solution difficult. To remedy this, we define sets C_d^ω, which contain the customers in C^ω reachable from depot d for $d = 1, ..., n$. Now, the above becomes

$$x_c^{\omega rd} = \begin{cases} 1 & \text{if robot } \quad r = 1, ..., r_{max} \text{ from hub } d \text{ serves customer } c, \\ & \text{where } d = 1, ..., n,\ c \in C_d^\omega, \omega \in \Omega; \\ 0 & \text{otherwise} \end{cases}$$

Furthermore, variables o^d reflect whether a robot hub is opened:

$$o^d = \begin{cases} 1 & \text{if robot hub } d \text{ is opened where } d = 1, ..., n \\ 0 & \text{otherwise} \end{cases}$$

To minimize the number of robot hubs, the following problem is solved:

$$min \sum_{d=1}^{n} o^d \tag{1}$$

Subject to:

$$\sum_{d=1:c \in C_d^\omega}^{n} \sum_{r=1}^{r_{max}} x_c^{\omega rd} = 1, \quad \text{for } c \in C^\omega, \omega \in \Omega \tag{2}$$

$$\sum_{c \in C_d^\omega} (t(d,c)(1 + \frac{t_f}{b}) + t_s) x_c^{\omega rd} \leq M, \quad \text{for } r = 1, ..., r_{max}, d = 1, ..., n, \omega \in \Omega \tag{3}$$

$$\sum_{r=1}^{r_{max}} x_c^{\omega rd} \leq o^d, \quad \text{for } c \in C_d^\omega, d = 1, ..., n, \omega \in \Omega \tag{4}$$

$$x_c^{\omega rd} \in \{0, 1\} \qquad \text{for } r = 1, ...r_{max}, d = 1, ...n, c \in C_d^\omega, \omega \in \Omega \tag{5}$$

$$o^d \in \{0, 1\} \qquad \text{for } d = 1, ...n \tag{6}$$

The objective function **(1)** minimizes the number of robot hubs. Constraint **(2)** ensures that all customer locations in all instances are assigned to a hub. Constraint **(3)** puts a limit on the maximum robot working time, which is based on the time required for the round trip to customer locations, recharging time, and service time. Constraint **(4)** ensures that if a robot serves a customer location in some instance, the corresponding robot hub is open. Constraints **(5)-(6)** define the domain of the variables.

Once we have solved the above problem, we know the minimum number of hubs needed for all instances. We refer to that value by p. To minimize operational robot cost, we next use the following model:

$$min \sum_{\omega \in \Omega} \sum_{d=1}^{m} \sum_{r=1}^{r_{max}} \sum_{c \in C_d^{\omega}} t(d,c) x_c^{\omega r d} \tag{7}$$

Subject to: Equations (2), (3), (5), (6)

$$\sum_{d=1}^{n} o^d = p \tag{8}$$

The objective function **(1)** minimizes the operational robot cost with p hubs. Constraint **(8)** guarantees that there are exactly as many open robot hubs as provided by our first model. We do not need an ordering of the tasks to be done by a particular robot as any order of the assigned deliveries will be feasible and have the same costs. Similarly, the deliveries can start anytime after the assigned packages have been delivered to their particular hub.

When solving this problem, we start with a high value of r_{max} to obtain the minimum cost value. Then, we iteratively reduce r_{max} across all instances to find the smallest value of r_{max} that achieves this minimum value. This identifies the minimum number of robots we need to potentially have available at each robot hub to minimize costs.

3.2.2 With Time Windows

Our second model considers customer time windows for robot deliveries. These time windows are denoted by $[e_c, l_c]$ for $c = 1 \ldots m$. For this model, we need to add new variables that consider the time a robot arrives at a customer:

$y_c^{\omega r d} =$ the time robot r leaves depot d to serve customer c for $r = 1, ..., r_{max}$, $d = 1, ..., n, c \in C_d^{\omega}, \omega \in \Omega$

$$z_{ij}^{\omega rd} = \begin{cases} 1 & \text{if customer } j \text{ follows customer } i \text{ for robot } r \text{ from depot } d, \text{for } r = 1, ..., r_{max}, \\ & d = 1, ..., n, \forall i, j \in C_d^{\omega} \text{such that time window of } j \text{ is the same or later than } i, \omega \in \Omega \\ 0 & \text{otherwise} \end{cases}$$

We also need a value L to represent the latest possible return to the depot after a delivery in the last time window. With these variables and new parameters, we can define the hub-minimizing variant of the problem. The objective remains as described in Equation (1). For constraints, we need Equations (2) – (5) as well as:

$$e_c x_c^{\omega rd} \leq y_c^{\omega rd} + \frac{t(d,c)x_c^{\omega rd}}{2} \quad \text{for } r = 1, ..., r_{max}, d = 1, ..., n, c \in C_d^{\omega}, \omega \in \Omega \tag{9}$$

$$y_c^{\omega rd} + \frac{t(d,c)x_c^{\omega rd}}{2} \leq l_c x_c^{\omega rd}, \quad \text{for } r = 1, ..., r_{max}, d = 1, ..., n, c \in C_d^{\omega}, \omega \in \Omega \tag{10}$$

$$y_j^{\omega rd} + (L + \frac{t_f}{b})(1 - z_{ij}^{\omega rd}) \geq y_i^{\omega rd} + t(d,i)(1 + \frac{t_f}{b}) + t_s, \quad \text{for } r = 1, ..., r_{max}$$
$$d = 1, ..., n, \forall i, j \in C_d^{\omega} \text{ where time window of } j \text{ equal or later than } i, \omega \in \Omega \tag{11}$$

$$x_i^{\omega rd} + x_j^{\omega rd} - z_{ij}^{\omega rd} - z_{ji}^{\omega rd} \leq 1, \quad \text{for } d = 1, ..., n, \forall i, j \in C_d^{\omega}$$
$$\text{where time window of } j \text{ is the same as } i, \omega \in \Omega \tag{12}$$

$$x_i^{\omega rd} + x_j^{\omega rd} - z_{ji}^{\omega rd} \leq 1, \quad \text{for } d = 1, ..., n, \forall i, j \in C_d^{\omega}$$
$$\text{where time window of } j \text{ equal or later than } i, \omega \in \Omega \tag{13}$$

$$y_c^{\omega rd} \in \mathcal{R}^+ \text{ for } r = 1, ..., r_{max}, d = 1, ..., n, c \in C_d$$

$$z_{ij}^{\omega rd} \in \{0, 1\} \text{ for } r = 1, ..., r_{max}, d = 1, ..., n, i, j \in C_d \text{ where time window of } j$$
$$\text{equal or later than } i, \omega \in \Omega. \tag{14}$$

Constraints **(9)** and **(10)** enforce customer time windows on deliveries in each instance. Constraint **(11)** ensures that the next customer cannot be served before service at the previous one has finished and the battery is fully recharged. Following the structure of Hernandez et al. (2014), constraints **(12-13)** connect the x and z variables. Finally, constraints **(14)** define the new variables.

Once we have solved the above, we know the minimum number of hubs we must open to service all customer locations in all instances. Again, we refer to that value by p. To minimize operational cost for time-window based deliveries, we can use Equation 7 as the objective, since time windows do not change how costs are incurred, and the following constraints: equations (2), (4)–(6), (8), (9 – 14).

3.3 Observations

Based on the parameters in Table 3.1, we can determine an upper bound on the number of hubs required to service all customers. We will need to solve the models in Section 3.1 to determine the optimal value and whether we can use less than this. We derive this bound to help understand which instance characteristics cause the solutions to get close to this bound in the computational experiments.

We will assume the service area is a square area of n^2 blocks. With this assumption, we can bound the number of hubs as follows. The upper bound on number of hubs required to cover all customers is given by $\lceil \frac{n}{\lfloor \frac{d_{max}}{2} \rfloor} \rceil^2$. To prove this, we first need to establish the value for d_{max}. Given the time range on one battery charge b and robot speed s, the farthest reachable customer from a hub is located $d_{max} = \lfloor \frac{b*s}{2*l} \rfloor$ blocks from the hub.

Proof. A maximum length of charge for a robot is b. The number of blocks it can cover on one battery charge is $\frac{b*s}{l}$. In addition, since robots are performing a round-trip basis, the farthest reachable customer can only be located half this distance away from a hub. Since customers and hubs are located at intersections, this number must be an integer and can be rounded down. $\square$

Now, we can prove our bound.

Proof. Horizontally, we need at most $\lceil \frac{n}{\lfloor \frac{d_{max}}{2} \rfloor} \rceil^2$ hubs to be able to serve all square areas of size $\lfloor \frac{d_{max}}{2} \rfloor$ by $\lfloor \frac{d_{max}}{2} \rfloor$. Again, we must take the floor of $\frac{d_{max}}{2}$ because of the fact that customers will be integer distances from hubs. We must take the ceiling of the result when divided by n if there are parts of the grid not covered by these squares. $\square$

Example: Let us consider an area of size 50 by 50 blocks, and a d_{max} of 5. Each hub can be used to cover a 2 ($\lfloor \frac{d_{max}}{2} \rfloor$) block by 2 block area. We need 25^2 of the squares to cover the whole service area.

4 Design of Experiments

In this section, we introduce the design of our computational experiments. We first discuss how we can make fair comparisons between the operational costs of our two-tier robot network and the costs arising from conventional single-tier truck-based deliveries. Next, we define datasets, costs, technical parameters of the considered delivery robots and trucks, as well as other parameters.

4.1 Comparing Robot-based and Truck-based Deliveries

As indicated in Section 3, we assume that the use of robot-based deliveries will require the use of a driver for first tier operations, but much less time since the driver will now only drive among the robot hubs rather than at all customers as in conventional single-tier operations. We model first tier operations as traveling salesman problem (TSP) from the depot to the robot hubs. We omit this formulation from the paper due to the well known nature of the TSP. We can use the TSP, rather than a VRP, since visiting all robot hubs always takes less than one driver's shift (assumed here as 8 hours). For this two-tier network, our total operational cost is based on a combination of

- the *gas cost* to perform the TSP from a depot to the robot hubs. The gas cost is based on the kilometers driven;
- the *driver cost*, which is based on the time for driving the TSP route plus the time to fill the packages at a hub, set at t_p per package, and
- the *cost of electricity* needed to serve all customers by the robots, which is based on the tier-two objective function, esp. the time robots are used.

We omit the purchase cost of the robot hubs and robots because they represent a fixed initial investment rather than an operational cost. We will look at the numbers required for purchase, though, in our experiments.

For conventional truck-based deliveries, we identify the least cost way for servicing all customers with a truck and driver. This must be solved as a VRP since visiting all customers takes more than one driver's shift time. We use Gunes Erdogan's Excel spreadsheet (Erdogan, 2017) to solve the corresponding VRPs with the assumption similarly to the robot case that all vehicles leave their depot at 8 am and need to return before 5 pm. For conventional truck-based deliveries, our total cost is based on a combination of

- the *gas cost* to visit all customers based on the mileage driven (s);

- the *driver cost*, which is based on the time for driving plus the time to deliver the packages at each customer, set at t_s per package.

We omit the investment cost for purchasing trucks and training drivers because we are focusing on operational costs.

To compare the cost per package with each approach, we simply divide the total cost, as described above, by the number of packages being delivered. Note that we do not compare our approaches computationally with those involving a delivery vehicle that drives to a neighborhood and deploys a set of robots. The reasons are two-fold: first, the objective in the closest paper (Boysen et al., 2018) involves minimizing late deliveries. With our design, deliveries will not be late. Second, because such technology does not yet exist, it is hard to model the cost per mile for operating such a vehicle.

4.2 Datasets

In our instances, we use Manhattan distances between all the nodes of the network. We consider downtown instances with a 2*2 kilometer square and 100*100 meter blocks as well as 16 possible robot hub locations (evenly spaced over the square), and suburban instances with a 10*10 km square and 36 possible depot locations (evenly spaced over the square). The customers are randomly distributed but are located at corner points of the blocks. We create instances with 100, 200 and 300 customers and generate 10 instances of each type with the smaller datasets being subsets of the larger instances. We consider variants without customer time windows, with 1-hour time windows with equal demand (8-9; 9-10; ...; 15-16) and with 2-hour time windows with unequally distributed demand (8-10; 10-12; 12-14; 14-16; with 25/10/10/55% demand distribution) following roughly the demand structure as reported by Köhler and Haferkamp (2019). All models were solved with Gurobi. The first-tier TSPs could be solved almost instantaneously, while the run time for the second-tier models strongly depended on the instance characteristics. Downtown instances required up to 70 minutes, while suburban instances could be solved in up to 7 minutes only.

4.3 Robot Parameters

We assume the baseline speed for a robot is 3 km/hour ("standard robot"), but we also consider faster robots with a speed of 6 km/hour ("fast robots"). Based on data provided by StarshipTechnologies (2015), we assume that the battery of a robot has a capacity of 8000 mAh. Based on this electric capacity and and average cost of energy in the U.S., a full recharge of the battery would cost around 1.4-2.3 cents. We simplify this to assume that a full recharge costs 2 cents. Our standard robots have a maximum operation time of $b = 2$ hours. Since they operate at double speed, our fast robots have a maximum operation time of $b = 1$ hour. According to Starship specifications, a full recharge of the battery would require 45 minutes. We assume that recharge time is a percentage of the full recharge time, t_f, resulting from the time required for the trip to the last customer and back to the robot hub relative to a full recharge. We note here that we did not test different costs for electricity, as it would not impact the structure of the solutions, but only the solution values. For example, a hike in electricity costs would not change the number of hubs, but only create a proportional increase in cost per package delivered by robots.

4.4 Other Parameters

For each package delivered to a robot hub, we assume a service time of $t_p = 1$ minute. Each package requires a service time of $t_s = 4$ minutes when being delivered to the customer (either by a robot or by a conventional delivery truck).

We consider two levels of driver wages. For the baseline, we assume that a truck driver is paid an hourly salary of $32.77 (Dayton, 2018), which is usually only paid for a driver of a big truck with trailer, but may be an indicator of how driver wages could develop in times of driver shortages. We refer to this as the “expensive driver wage”. As an alternative, we consider the wage a last-mile truck driver is currently paid, which corresponds to an hourly salary of $13.90. We call this “cheap driver wage” and investigate this for some of the more challenging time-window based experiments.

For the truck parameters, we follow the assumption that a standard UPS truck consumes 26 liters of gas per 100 kilometers on average (Powell (2015)). As of November 2018, Iowa gas prices were $2.84 per gallon, so we use a value of 19.5 cents of gas cost per kilometer. We assume an average speed of 30 km/h for trucks in both downtown and suburban environments.

5 Computational Results

In the following, we report the results of our experiments and try to develop insights about when robot-based deliveries are beneficial compared to conventional deliveries. We also discuss briefly about the investments required to convert to two-tiered robot deliveries.

5.1 Summary

A summary of all results is shown in Table 2. Each instance is described by customer location (downtown vs. surburbs), the assumed speed of the delivery robots (3 vs. 6 km/h),

location	speed	driver	time windows	# cust	# hubs	# robots	first tier cost	second tier cost	cost per pkg (robot)	cost per pkg (conv)	savings
downtown	3	exp	no tw	100	1.0	16.8	57.20	0.89	0.58	2.45	76.3%
downtown	3	exp	no tw	200	2.0	14.8	114.63	1.54	0.57	2.37	75.9%
downtown	3	exp	no tw	300	2.0	20.0	171.57	1.64	0.58	2.33	75.2%
suburbs	3	exp	no tw	100	13.0	3.1	108.63	1.00	1.11	3.45	67.9%
suburbs	3	exp	no tw	200	13.0	4.8	163.25	1.97	0.84	3.05	72.6%
suburbs	3	exp	no tw	300	13.0	7.3	217.87	2.97	0.75	2.88	74.1%
downtown	6	exp	no tw	100	1.0	11.3	57.20	0.89	0.58	2.45	76.3%
downtown	6	exp	no tw	200	1.0	18.2	113.10	1.46	0.57	2.37	75.9%
downtown	6	exp	no tw	300	2.0	16.8	166.44	2.57	0.56	2.33	76.0%
suburbs	6	exp	no tw	100	13.0	2.0	108.63	1.00	1.10	3.45	68.1%
suburbs	6	exp	no tw	200	13.0	3.5	163.25	1.98	0.83	3.05	72.8%
suburbs	6	exp	no tw	300	13.0	4.6	217.87	2.98	0.74	2.88	74.3%
downtown	3	exp	1-hour	100	1.0	16.2	58.48	0.72	0.59	5.24	88.7%
downtown	3	exp	1-hour	200	2.0	16.0	116.95	1.10	0.64	3.91	83.6%
suburbs	3	exp	1-hour	100	13.0	4.2	108.63	1.00	1.10	8.45	87.0%
suburbs	3	exp	1-hour	200	13.0	6.1	163.25	1.97	0.83	6.74	87.7%
downtown	3	chp	1-hour	100	1.0	16.2	25.14	0.72	0.26	2.29	88.6%
downtown	3	chp	1-hour	200	2.0	15.7	50.28	1.10	0.26	1.71	85.0%
suburbs	3	chp	1-hour	100	13.0	4.2	50.77	1.00	0.52	3.88	86.7%
suburbs	3	chp	1-hour	200	13.0	6.1	73.93	1.97	0.38	3.10	87.8%
downtown	3	exp	unequal dem	100	2.0	17.1	57.20	0.82	0.58	7.52	92.3%
suburbs	3	exp	unequal dem	100	13.0	4.2	108.63	1.00	1.10	10.50	89.6%
suburbs	3	exp	unequal dem	200	13.0	6.5	163.25	1.97	0.83	8.16	89.9%

Table 2: Summary Results

the driver wage level (cheap vs. expensive), the type of time windows considered (no time windows vs. 1-hour with equal demand vs. 2-hour time windows with unequal demand), and the number of customers (# cust). In terms of results, we show the average first and second tier costs, the average number of robot hubs (# hubs), the average number of required robots (# robots), the average cost per package for robot-based deliveries (cost per pkg (robot)), the average cost per package for conventional deliveries (cost per pkg (conv)), and the percentage savings when using delivery robots relative to conventional deliveries. Note that we use much less robot hubs than precomputed by our bound, which is 4 robot hubs for downtown instances and 49 robot hubs for suburban instances. Cost savings range from 67.9% to 92.3%.

Insight: cost per package for the two-tiered robot-based deliveries is much less than the conventional single tier truck-based system across all experiments. This indicates that two-tier robot-based delivery systems are quite promising.

To understand more about the results, we will next break down the experiments by category.

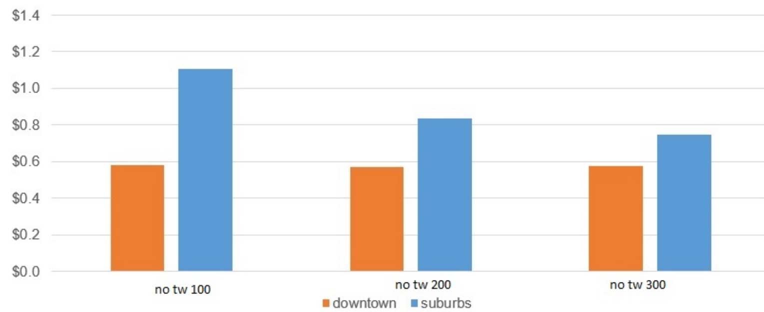


Figure 2: Total Cost per Package for Robot-Based Deliveries (downtown vs. suburbs, w/o time windows)

5.2 No Time Windows

We first focus on instances with our baseline robot speeds (3 km/h) and baseline driver costs (expensive). We present the results for these instances without time windows graphically in Figure 2. Here we see that in downtown areas, the delivery of one package costs about $0.58 on average for robot-based deliveries without time windows. With increasing customer density, costs per package do not decrease much more.

Insight: cost per package for the two-tiered robot-based deliveries without time windows is fairly stable at $0.58 per package in downtown areas.

However, for suburban areas, we see significant economies-of-scale with increasing customer density. While small instances with low customer density create relatively high costs of $1.11 per package, a high customer density leads to significantly cheaper costs per package of $0.75.

Insight: cost per package for the two-tiered robot-based deliveries without time windows reduces in suburbs as delivery density increases. This indicates that

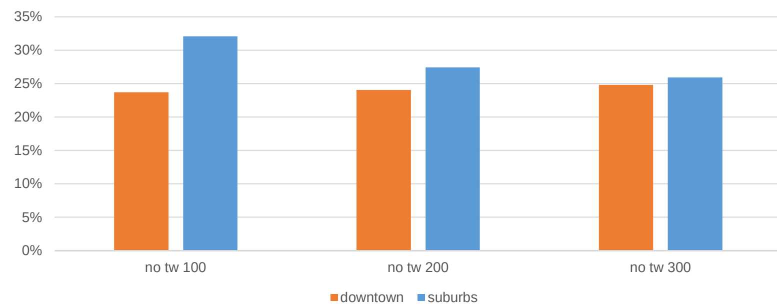


Figure 3: Relative Cost per Package for Robot-Based Deliveries (downtown vs. suburbs, w/o time windows)

robot-based deliveries will become more profitable/create lower costs in suburbs as more customers and/or companies adopt this delivery technology.

To get a better idea of the savings, Figure 3 shows the relative value of cost-per-package from robot-based deliveries compared to conventional truck-based deliveries when we focus on our baseline robot speed (3 km/h). The two-tier delivery network can be operated at only about 24% of the cost of a conventional, truck-based delivery-based network in downtown areas. For locations in suburban areas, the cost reduction can vary from about 26-32% depending on the customer density.

Insight: robot-based deliveries can operate for about 24-32% of the cost of conventional truck-based deliveries with sufficient customer density. This represents a huge savings for delivery companies.

5.3 Robot Speeds

We also investigated the impact of robots with different technology, in particular with different speeds of 3 km/h and 6 km/h. We keep the driver cost as its baseline value and again use no time windows. Cost per package for the different instances is shown in Figure 4 for different speeds. Generally, there are no significant differences for downtown instances, where we again see a cost level of about $0.58 per package. Somewhat similar behavior can be observed for higher speeds. Here, relative costs can go down from $1.10 for the 100-customer instances (as also seen with robots with standard speeds) to as low as $0.74 for the 300-customer instances.

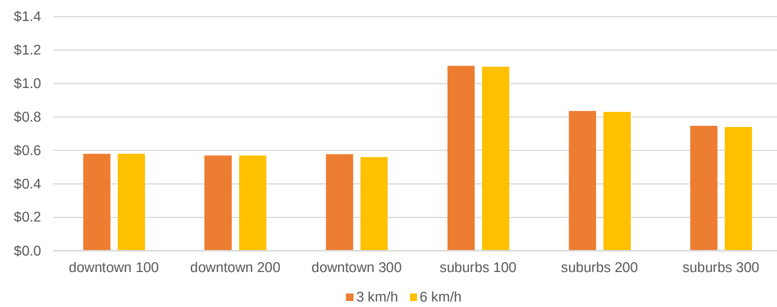


Figure 4: Total Cost per Package for Robot-Based Deliveries with Different Speeds (standard vs. high speed)

Insight: higher robot speed does not generate significantly more savings compared to lower speed.

5.4 Time Windows

To understand the impact of time windows, we compare the two-tier robot-based delivery costs with conventional truck-based deliveries in Figure 5. We assume the baseline robot speeds and driver costs. The bars on the left represent the savings with no time windows, and the bars on the right represent the savings when customers have one hour time windows. As indicated earlier, in our baseline time window experiments, customers are randomly assigned time windows such that they are equally likely to receive any of the available time windows. The results in Figure 5 reflect that time windows increase the amount of savings, where robot-based deliveries can save up to 89% of the cost for conventional deliveries. The lower savings for downtown as a result of going from 100 to 200 customers is not due to the change in cost of robot deliveries but the decreased cost per package for conventional deliveries due to higher customer densities.

Insight: the use of time windows increases the savings vs. conventional truck-based deliveries, with savings of up to 89%.

Savings increase even more when time-window based deliveries become more complex as shown in Figure 6. For the results of the unequal demand scenario reported here, we can save operational cost up to 92.3% of conventional deliveries. Hence, investing into

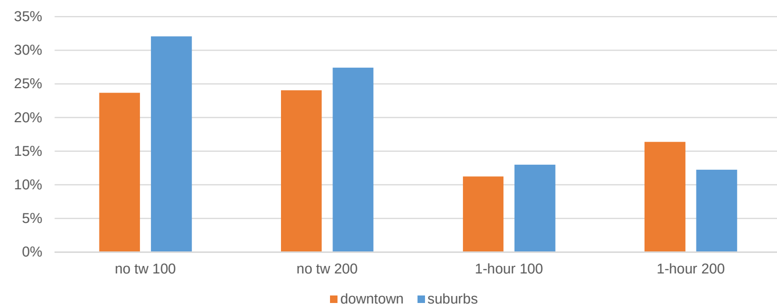


Figure 5: Relative Cost per Package for Robot-Based Deliveries (downtown vs. suburbs, with equal time windows)

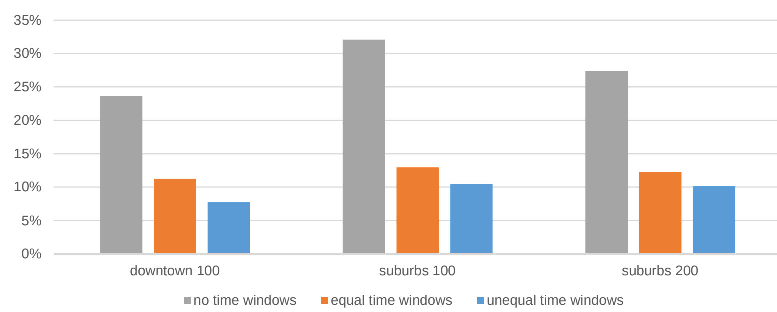


Figure 6: Relative Cost per Package for Robot-Based Deliveries with No/Equal/Unequal Time Windows

automation of the most expensive part of the delivery network pays off in such a situation with complex and costly customer service.

Insight: robot-based deliveries are even more valuable with unequally distributed demand for time windows. This is when conventional deliveries cost the most per package.

5.5 Driver Wages

While the total costs are of course different when comparing expensive and cheap driver wages, relative cost comparisons remain stable, since only a small part of our two-tier network is operated manually.

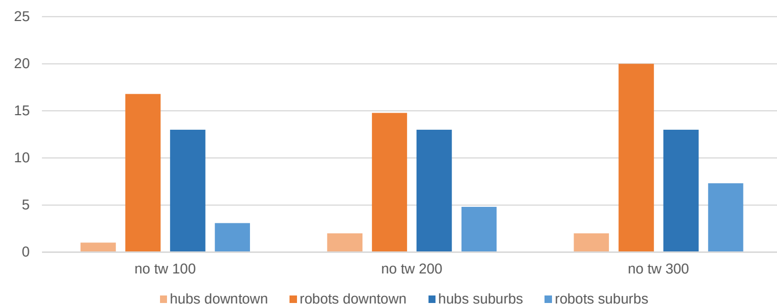


Figure 7: Investment cost: #robot hubs vs. #robots (downtown vs. suburbs, w/o time windows)

Insight: driver wages impact operational costs of robot deliveries, but have little impact on percentage savings vs. conventional deliveries.

5.6 Initial Investments

We will conclude with an analysis of the investments required for our two-tier robot-based delivery network without time windows. Figure 7 shows the investment costs in terms of the number of hubs required for downtown and suburban deliveries for different totals of customers. For downtowns, one or two hubs are sufficient to handle robot-based deliveries for all customers, since the battery range is sufficient to reach all potential customer locations. With increasing number of customers, simply activating more robots is enough to service all customers. This is good news, since potential locations for robot hubs are likely to be rare in downtown areas.

For suburban delivery, many more robot hubs are required to reach all potential customer locations. With much less customer density, 13 robot hubs are required in our experiments, but they maintain significantly less robots on average. These suburban robot hubs need to be positioned carefully to ensure feasible service for all potential customer locations.

Insight: downtown areas require less robot hubs than suburbs, but many more robots per hub.

6 Conclusion and Future Work

Our results have shown the amazing potential of robot-based deliveries to reduce operational costs of last-mile deliveries. We have shown that they reduce costs the most when conventional deliveries cost the most, i.e. when customer density is low and service expectations are high. Organizing the delivery network in tiers can save significant amounts of operational costs and help maintain customer service.

A recent article in the Seattle Times (Korman, 2019) refers to an estimate of $ 2.50 per delivery completed by USPS for Amazon, which is quite similar to the values found here for downtown deliveries without time windows. The same Seattle Times article mentions an estimate that aerial drones could save $0.76 bringing the cost down to $1.74. For downtown areas without time windows, our paper shows robots could bring down the cost to well under a dollar. This indicates that robot-based deliveries are a very promising solution for innovative last-mile deliveries.

In the future, we intend to expand our work given the promising results we have seen so far. In the current work, the MIPs were fairly quick to solve. For larger instances, we could reduce runtimes by preventing symmetry among the assignment choices for the different robots for a particular location. Furthermore, we are particularly interested in seeing how the stochastic nature of the use of sidewalk robots would impact savings. For example, currently sidewalk robots must stop if any person gets in their path. This will make their travel times variable. But some of this variability may be time-dependent, such as with higher numbers of pedestrians at the start of a work or school day or on some roads. We will look at different ways to model this variability to identify how it impacts the performance of sidewalk robots.

Also, as different technologies develop regarding multi-compartment and different battery life capabilities, we can expand in this direction as well.

7 Appendix

In the following, we present our detailed results for each instance of each experiment.

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	1	18	93.33	0.74	5.23	5.97	243.93
2	1	17	91.67	0.70	5.36	6.06	245.48
3	1	17	92.8	0.74	5.36	6.10	243.93
4	1	16	86.8	0.70	5.23	5.94	245.22
5	1	17	88	0.75	5.23	5.98	245.22
6	1	17	87.73	0.77	5.23	6.00	245.99
7	1	16	87.33	0.73	5.23	5.96	243.67
8	1	18	93.2	0.76	5.23	5.99	244.96
9	1	16	87.8	0.71	5.23	5.95	244.96
10	1	16	86.26	0.73	5.23	5.96	245.22
avg	1	16.8	89.49	0.73	5.26	5.99	244.86
package				0.01		0.06	2.45
200							
1	2	15	153.13	1.52	113.10	114.61	471.92
2	2	15	158.07	1.56	113.10	114.66	472.43
3	2	15	156.67	1.55	113.10	114.65	473.97
4	2	15	158.07	1.56	113.10	114.66	472.95
5	2	14	150.67	1.49	113.10	114.59	473.20
6	2	15	157.07	1.55	113.10	114.65	473.72
7	2	15	158.40	1.57	113.10	114.66	473.72
8	2	15	153.13	1.52	113.10	114.61	472.43
9	2	15	160.33	1.59	113.10	114.68	473.46
10	2	14	148.33	1.47	113.10	114.56	474.75
avg	2	14.8	155.39	1.54	113.10	114.63	473.25
package				0.01		0.57	2.37
300							
1	2	20	166.80	1.65	171.57	173.23	699.39
2	2	20	163.13	1.62	171.57	173.19	699.77
3	2	20	167.80	1.66	171.57	173.24	699.77
4	2	20	168.13	1.66	171.57	173.24	699.39
5	2	20	166.27	1.65	171.57	173.22	699.39
6	2	20	164.00	1.62	171.57	173.20	700.54
7	2	20	160.80	1.59	171.57	173.17	699.00
8	2	20	167.67	1.66	171.57	173.23	699.77
9	2	20	167.07	1.65	171.57	173.23	700.54
10	2	20	167.07	1.65	171.57	173.23	699.77
avg	2	20	165.87	1.64	171.57	173.22	699.73
package				0.01		0.58	2.33

Table 3: Detailed Results Downtown, No Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	13	4	96.87	0.96	108.63	109.59	343.22
2	13	3	103.87	1.03	108.63	109.66	347.59
3	13	3	98.93	0.98	108.63	109.61	350.17
4	13	3	103.87	1.03	108.63	109.66	347.08
5	13	3	100.40	0.99	108.63	109.63	347.08
6	13	3	103.67	1.03	108.63	109.66	345.02
7	13	3	101.73	1.01	108.63	109.64	342.45
8	13	3	101.73	1.01	108.63	109.64	338.33
9	13	3	99.00	0.98	108.63	109.61	347.08
10	13	3	102.47	1.01	108.63	109.65	341.42
avg	13	3.1	101.25	1.00	108.63	109.64	344.95
package				0.01		1.10	3.45
200							
1	13	6	196.20	1.94	163.25	165.19	609.02
2	13	5	201.73	2.00	163.25	165.25	612.11
3	13	4	201.67	2.00	163.25	165.25	607.22
4	13	5	205.07	2.03	163.25	165.28	611.59
5	13	5	197.87	1.96	163.25	165.21	611.59
6	13	4	196.87	1.95	163.25	165.20	612.88
7	13	4	199.27	1.97	163.25	165.22	612.88
8	13	6	203.20	2.01	163.25	165.26	605.42
9	13	4	192.73	1.91	163.25	165.16	615.45
10	13	5	200.20	1.98	163.25	165.23	607.99
avg	13	4.8	199.48	1.97	163.25	165.23	610.61
package				0.01		0.83	3.05
300							
1	13	7	289.93	2.87	217.87	220.74	869.93
2	13	8	304.13	3.01	217.87	220.88	864.01
3	13	7	314.00	3.11	217.87	220.98	865.04
4	13	7	302.80	3.00	217.87	220.87	860.41
5	13	8	293.73	2.91	217.87	220.78	860.41
6	13	7	295.60	2.93	217.87	220.79	869.16
7	13	7	288.53	2.86	217.87	220.72	867.87
8	13	8	309.40	3.06	217.87	220.93	859.64
9	13	7	296.33	2.93	217.87	220.80	872.24
10	13	7	306.40	3.03	217.87	220.90	866.07
avg	13	7.3	300.09	2.97	217.87	220.84	865.48
package				0.01		0.74	2.88

Table 4: Detailed Results Suburbs, No Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	1	12	46.67	0.92	57.20	58.13	243.93
2	1	11	45.84	0.91	57.20	58.11	245.48
3	1	12	46.40	0.92	57.20	58.12	243.93
4	1	11	43.40	0.86	57.20	58.06	245.22
5	1	11	44.00	0.87	57.20	58.07	245.22
6	1	11	43.87	0.87	57.20	58.07	245.99
7	1	11	43.67	0.86	57.20	58.07	243.67
8	1	12	46.60	0.92	57.20	58.12	244.96
9	1	11	43.90	0.87	57.20	58.07	244.96
10	1	11	43.13	0.85	57.20	58.06	245.22
avg	1	11.3	44.75	0.89	57.20	58.09	244.86
package				0.01		0.58	2.45
200							
1	1	19	75.10	1.49	113.10	114.58	471.92
2	1	18	73.86	1.46	113.10	114.56	472.43
3	1	18	74.26	1.47	113.10	114.57	473.97
4	1	18	70.67	1.40	113.10	114.49	472.95
5	1	18	73.10	1.45	113.10	114.54	473.20
6	1	18	73.70	1.46	113.10	114.55	473.72
7	1	18	74.37	1.47	113.10	114.57	473.72
8	1	18	73.50	1.46	113.10	114.55	472.43
9	1	19	75.07	1.49	113.10	114.58	473.46
10	1	18	71.63	1.42	113.10	114.51	474.75
avg	1	18.2	73.53	1.46	113.10	114.55	473.25
package				0.01		0.57	2.37
300							
1	2	17	131.77	2.61	166.44	169.05	699.39
2	2	17	132.00	2.61	166.44	169.05	699.77
3	2	17	130.43	2.58	166.44	169.02	699.77
4	2	17	126.73	2.51	166.44	168.95	699.39
5	2	17	125.66	2.49	166.44	168.93	699.39
6	2	17	130.46	2.58	166.44	169.02	700.54
7	2	16	129.07	2.56	166.44	168.99	699.00
8	2	17	131.36	2.60	166.44	169.04	699.77
9	2	17	133.60	2.65	166.44	169.08	700.54
10	2	16	125.83	2.49	166.44	168.93	699.77
avg	2	16.8	129.69	2.57	166.44	169.01	699.73
package				0.01		0.56	2.33

Table 5: Detailed Results Downtown, High Speed, No Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	13	2	48.43	0.96	108.63	109.59	343.22
2	13	2	51.93	1.03	108.63	109.66	347.59
3	13	2	49.47	0.98	108.63	109.61	350.17
4	13	2	51.93	1.03	108.63	109.66	347.08
5	13	2	50.20	0.99	108.63	109.63	347.08
6	13	2	51.80	1.03	108.63	109.66	345.02
7	13	2	50.87	1.01	108.63	109.64	342.45
8	13	2	50.87	1.01	108.63	109.64	338.33
9	13	2	49.50	0.98	108.63	109.61	347.08
10	13	2	50.73	1.00	108.63	109.64	341.42
avg	13	2	50.57	1.00	108.63	109.64	344.95
package				0.01		1.10	3.45
200							
1	13	4	98.10	1.94	163.25	165.19	609.02
2	13	3	100.87	2.00	163.25	165.25	612.11
3	13	3	100.83	2.00	163.25	165.25	607.22
4	13	4	102.53	2.03	163.25	165.28	611.59
5	13	3	98.93	1.96	163.25	165.21	611.59
6	13	3	98.43	1.96	163.25	165.21	612.88
7	13	4	99.63	1.97	163.25	165.22	612.88
8	13	4	101.60	2.01	163.25	165.26	605.42
9	13	3	96.37	1.91	163.25	165.16	615.45
10	13	4	100.10	1.98	163.25	165.23	607.99
avg	13	3.5	99.74	1.98	163.25	165.23	610.61
package				0.01		0.83	3.05
300							
1	13	4	145.10	2.87	217.87	220.74	869.93
2	13	4	153.10	3.03	217.87	220.90	864.01
3	13	5	157.00	3.11	217.87	220.98	865.04
4	13	5	151.40	3.00	217.87	220.87	860.41
5	13	5	146.87	2.91	217.87	220.78	860.41
6	13	4	147.80	2.93	217.87	220.80	869.16
7	13	4	144.27	3.06	217.87	220.93	867.87
8	13	5	154.70	2.93	217.87	220.80	859.64
9	13	5	148.17	2.93	217.87	220.80	872.24
10	13	5	153.20	3.03	217.87	220.90	866.07
avg	13	4.6	150.16	2.98	217.87	220.85	865.48
package				0.01		0.74	2.88

Table 6: Detailed Results Suburbs, High Speed, No Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	con-ventional $
1	1	17	75.80	0.75	58.48	59.23	523.51
2	1	16	73.00	0.70	58.48	59.18	524.59
3	1	16	75.06	0.74	58.48	59.22	523.59
4	1	16	71.00	0.70	58.48	59.18	523.12
5	1	16	73.73	0.73	58.48	59.21	524.69
6	1	16	73.26	0.73	58.48	59.20	523.28
7	1	16	69.60	0.69	58.48	59.16	523.34
8	1	17	78.13	0.77	58.48	59.25	523.80
9	1	16	70.73	0.70	58.48	59.18	530.03
10	1	16	70.13	0.69	58.48	59.17	523.99
avg	1	16.2	73.04	0.72	58.48	59.20	524.39
package				0.01		0.59	5.24
200							
1	2	17	116.33	1.15	116.95	118.10	721.65
2	2	15	107.33	1.06	116.95	118.01	789.97
3	2	16	114.87	1.14	116.95	118.09	787.42
4	2	15	112.33	1.11	116.95	118.06	785.91
5	2	17	115.80	1.15	116.95	118.10	787.77
6	2	15	106.33	1.05	116.95	223.28	790.24
7	2	16	107.80	1.07	116.95	118.02	786.96
8	2	17	115.87	1.15	116.95	118.10	786.03
9	2	16	109.87	1.09	116.95	118.04	788.98
10	2	16	107.93	1.07	116.95	118.02	787.54
avg	2	16	111.45	1.10	116.95	128.58	781.25
package				0.01		0.64	3.91

Table 7: Detailed Results Downtown, 1-hour Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	con-ventional $
1	13	4	96.87	0.96	108.63	109.59	878.09
2	13	5	103.87	1.03	108.63	109.66	850.06
3	13	4	98.93	0.98	108.63	109.61	840.82
4	13	4	103.87	1.03	108.63	109.66	844.74
5	13	5	100.40	0.99	108.63	109.63	846.20
6	13	4	103.67	1.03	108.63	109.66	839.96
7	13	4	101.73	1.01	108.63	109.64	840.15
8	13	4	101.73	1.01	108.63	109.64	830.89
9	13	4	99.00	0.98	108.63	109.61	837.46
10	13	4	101.47	1.00	108.63	109.64	842.49
avg	13	4.2	101.15	1.00	108.63	109.64	845.09
package				0.01		1.10	8.45
200							
1	13	6	196.20	1.94	163.25	165.19	1374.32
2	13	6	201.73	2.00	163.25	165.25	1375.18
3	13	6	201.66	2.00	163.25	165.25	1345.10
4	13	7	205.13	2.03	163.25	165.28	1380.27
5	13	6	197.86	1.96	163.25	165.21	1152.00
6	13	6	196.86	1.95	163.25	165.20	1380.67
7	13	6	199.26	1.97	163.25	165.22	1380.17
8	13	6	203.20	2.01	163.25	165.26	1371.77
9	13	6	192.73	1.91	163.25	165.16	1367.42
10	13	6	200.20	1.98	163.25	165.23	1362.48
avg	13	6.1	199.48	1.97	163.25	165.23	1348.94
package				0.01		0.83	6.74

Table 8: Detailed Results Suburbs, 1-hour Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	1	17	75.80	0.75	25.14	25.89	228.19
2	1	16	73.00	0.70	25.14	25.84	228.90
3	1	16	75.06	0.74	25.14	25.88	228.27
4	1	16	71.00	0.70	25.14	25.84	227.81
5	1	16	73.73	0.73	25.14	25.87	228.81
6	1	16	73.26	0.73	25.14	25.86	227.96
7	1	16	69.60	0.69	25.14	25.83	228.21
8	1	17	78.13	0.77	25.14	25.91	228.68
9	1	16	70.73	0.70	25.14	25.84	231.32
10	1	16	70.13	0.69	25.14	25.83	228.49
avg	1	16.2	73.04	0.72	25.14	25.86	228.66
package				0.01		0.26	2.29
200							
1	2	16	116.33	1.15	50.28	51.43	315.94
2	2	16	107.33	1.06	50.28	51.34	345.39
3	2	16	114.87	1.14	50.28	51.41	343.60
4	2	15	112.33	1.11	50.28	51.39	342.46
5	2	16	115.80	1.15	50.28	51.42	343.94
6	2	15	106.33	1.05	50.28	51.33	345.66
7	2	16	108.50	1.07	50.28	51.35	343.51
8	2	16	115.87	1.15	50.28	51.42	342.96
9	2	15	109.87	1.09	50.28	51.36	344.59
10	2	16	107.93	1.07	50.28	51.34	344.09
avg	2	15.7	111.52	1.10	50.28	51.38	341.22
package				0.01		0.26	1.71

Table 9: Detailed Results Downtown, 1-hour Time Windows, Cheap Drivers

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	13	4	96.87	0.96	50.77	51.73	402.57
2	13	5	103.87	1.03	50.77	51.79	392.46
3	13	4	98.93	0.98	50.77	51.75	385.10
4	13	4	103.87	1.03	50.77	51.79	388.09
5	13	5	100.40	0.99	50.77	51.76	390.11
6	13	4	103.67	1.03	50.77	51.79	384.25
7	13	4	101.73	1.01	50.77	51.77	385.38
8	13	4	101.73	1.01	50.77	51.77	381.41
9	13	4	99.00	0.98	50.77	51.75	385.33
10	13	4	101.47	1.00	50.77	51.77	385.46
avg	13	4.2	101.15	1.00	50.77	51.77	388.02
package				0.01		0.52	3.88
200							
1	13	6	196.20	1.94	73.93	75.88	630.46
2	13	6	201.73	2.00	73.93	75.93	628.30
3	13	6	201.66	2.00	73.93	75.93	614.83
4	13	7	205.13	2.03	73.93	75.96	632.45
5	13	6	197.86	1.96	73.93	75.89	538.35
6	13	6	196.86	1.95	73.93	75.88	634.36
7	13	6	199.26	1.97	73.93	75.91	632.92
8	13	6	203.20	2.01	73.93	75.94	631.12
9	13	6	192.73	1.91	73.93	75.84	627.71
10	13	6	200.20	1.98	73.93	75.92	625.04
avg	13	6.1	199.48	1.97	73.93	75.91	619.55
package				0.01		0.38	3.10

Table 10: Detailed Results Suburbs, 1-hour Time Windows, Cheap Drivers

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	2	18	84.40	0.84	2.59	57.20	754.79
2	2	17	83.07	0.82	2.59	57.20	736.85
3	2	17	81.13	0.80	2.59	57.20	752.61
4	2	17	79.27	0.78	2.59	57.20	753.81
5	2	17	84.80	0.84	2.59	57.20	754.44
6	2	17	84.27	0.83	2.59	57.20	752.92
7	2	17	78.73	0.78	2.59	57.20	754.56
8	2	17	88.60	0.88	2.59	57.20	753.08
9	2	17	82.40	0.82	2.59	57.20	751.63
10	2	17	79.73	0.82	2.59	57.20	752.84
avg	2	17.1	82.64	0.82	2.59	57.20	751.75
package				0.01		0.57	7.52

Table 11: Detailed Results Downtown Unequal Time Windows

100	# hubs	# robots	robot time	robot working ($)	tsp cost ($)	total cost ($)	conventional $
1	13	5	96.86	0.96	108.63	109.59	1047.51
2	13	4	103.86	1.03	108.63	109.66	1039.12
3	13	4	98.93	0.98	108.63	109.61	1037.48
4	13	4	103.86	1.03	108.63	109.66	1055.98
5	13	5	100.40	0.99	108.63	109.63	1041.83
6	13	4	103.66	1.03	108.63	109.66	1055.32
7	13	4	101.73	1.01	108.63	109.64	1049.08
8	13	4	101.73	1.01	108.63	109.64	1050.17
9	13	4	99.00	0.98	108.63	109.61	1078.07
10	13	4	101.46	1.00	108.63	109.64	1048.63
avg	13	4.2	101.15	1.00	108.63	109.64	1050.32
package				0.01		1.10	10.50
200							
1	13	7	196.20	1.94	163.25	165.19	1628.65
2	13	7	201.73	2.00	163.25	165.25	1594.29
3	13	7	201.67	2.00	163.25	165.25	1620.92
4	13	6	205.07	2.03	163.25	165.28	1699.02
5	13	6	197.86	1.96	163.25	165.21	1628.42
6	13	6	196.86	1.95	163.25	165.20	1633.17
7	13	6	199.26	1.97	163.25	165.22	1630.11
8	13	8	203.20	2.01	163.25	165.26	1635.42
9	13	6	192.73	1.91	163.25	165.16	1613.92
10	13	6	200.20	1.98	163.25	165.23	1626.10
avg	13	6.5	199.48	1.97	163.25	165.23	1631.00
package				0.01		0.83	8.16

Table 12: Detailed Results Suburban Unequal Time Windows

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