

A Scalable Last-Mile Delivery Service: From Simulation to Scaled Experiment

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Abstract—In this paper, we investigate the problem of a last-mile delivery service that selects up to N available vehicles to deliver M packages from a centralized depot to M delivery locations. The objective of the last-mile delivery service is to jointly maximize customer satisfaction (minimize delivery time) and minimize operating cost (minimize total travel time) by selecting the optimal number of vehicles to perform the deliveries. We model this as an assignment (vehicles to packages) and path planning (determining the delivery order and route) problem, which is equivalent to the NP-hard multiple traveling salesperson problem. We propose a scalable heuristic algorithm, which sacrifices some optimality to achieve a reasonable computational cost for a high number of packages. The algorithm combines hierarchical clustering with a greedy search. To validate our approach, we compare the results of our simulation to experiments in a 1:25 scale robotic testbed for future mobility systems.

I. INTRODUCTION

In a rapidly urbanizing world, we need to make fundamental transformations in how we use and access transportation [1]. With the meteoric rise of the e-commerce industry, last-mile delivery, especially parcel delivery, has attracted considerable attention [2]. Last-mile delivery refers to the last step in a supply chain, where goods or people are transported from a centralized hub to their final destination. In general, last-mile delivery is considered the least efficient part of the entire logistics chain, and it has been an area of significant research [3]–[9]. Additionally, as our energy, transportation, and cyber networks integrate further, and interact with human operators, we are witnessing a new level of complexity [10] in transportation systems. In this environment, last-mile delivery firms will need to meet ever-increasing fulfillment demands as efficiently as possible.

This paper investigates the problem of last-mile delivery through a centralized delivery service, which we model as a joint assignment (assigning vehicles to packages) and path planning (determining delivery order and route) problem with a variable number of vehicles. These problems are coupled, as the cost of the assignment is dependent on the

path taken by each of the vehicles. This is similar to the multiple traveling salesperson problem (mTSP) [11], [12], a generalization of the NP-hard traveling salesperson problem (TSP). As a result, there have been many approaches to generate solutions to mTSP for vehicle routing and last-mile delivery problems [4], [13]–[17]. Recent efforts in this area include ant colony optimization to solve mTSP with capacity and time window constraints for vehicle routing [13], fuzzy logic approaches for multi-objective mTSP [18], and data-driven graph-theoretic approaches to bus scheduling [19]. Other efforts have proposed augmenting last-mile delivery with cargo bicycles [20] and drones [21], [22] to decrease the number of cars and vans required and further reduce delivery times. However, to the best of our knowledge, validation of a last-mile delivery service in a physical experiment has not yet been reported in the literature. We seek to fill this gap by validating a heuristic algorithm for last-mile delivery in a scaled physical testbed.

Our first contribution is a fast online algorithm to generate the assignment of vehicles to deliveries as well as the routes of each vehicle. Online algorithms are critical in many logistic applications, particularly on-demand meal delivery. This is based on our previous work, where agents are assigned to goals and generate trajectories to create a desired formation [23], [24]. Our second contribution is the experimental validation of a last-mile delivery algorithm in a physical testing environment, which, to the best of our knowledge, has not yet been addressed in the literature.

The remainder of the paper is organized as follows. In Section II, we present some mathematical preliminaries on graph theory, and in Section III, we formulate the last-mile delivery service problem along with our modeling framework. In Section IV, we discuss our scalable heuristic solution, and in Section V, we present simulation results alongside the experimental validation in our 1:25 scale testbed. Finally, we draw concluding remarks in Section VI.

II. PRELIMINARIES

In this section, we present preliminary mathematical material that describes how we model our urban road network as a mathematical graph.

Definition 1. Our urban roadway network is represented by a directed graph, denoted $\mathcal{U} = (\mathcal{V}, \mathcal{E})$, which consists of:

- A set of nodes, $\mathcal{V} \subset \mathbb{N}$, corresponding to the locations where 1) two road segments join or separate, e.g., merging zones, intersections, roundabouts, entry and

This research was supported by the Sociotechnical Systems Center (SSC) at the University of Delaware.

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exit ramps, and 2) locations where the road network transitions between straight-line and arc segments.

- A set of directed edges, $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$, which contains pairs of nodes that are connected by a one-way road segment.

For every edge $e \in \mathcal{E}$ there is an associated cost, $c(e) \in \mathbb{R}_{>0}$, which corresponds to the amount of time taken for a vehicle to travel the length of the edge. Next, we define the motion of vehicles through the road network in terms of paths.

Definition 2. For a graph $\mathcal{U} = (\mathcal{V}, \mathcal{E})$, a path of length $\ell \in \mathbb{N}$ is a sequence of nodes, denoted $\mathcal{P} = (p_1, \dots, p_\ell)$, where $p_1, \dots, p_\ell \in \mathcal{V}$, and there exists a corresponding edge $(p_k, p_{k+1}) \in \mathcal{E}$ for all $k \in \{1, \dots, \ell - 1\}$. The total cost of a path \mathcal{P} is equal to the sum of the costs of its edges, i.e., $c(\mathcal{P}) = \sum_{k=1}^{\ell-1} c((p_k, p_{k+1}))$.

In the next section, we formulate our last-mile delivery service, which manages the delivery of packages to customers from a centralized depot. The objective of our delivery service is to jointly minimize cost and maximize customer satisfaction, i.e., jointly minimize the total travel time and average delivery time.

III. PROBLEM FORMULATION

Our delivery service consists of $N \in \mathbb{N}$ vehicles that can be used to deliver $M \in \mathbb{N}$ packages to nodes located on the urban road network \mathcal{U} . Let $\mathcal{N} := \{1, \dots, N\}$ index the available delivery vehicles, and let $\mathcal{D} \subset \mathcal{V}$ denote the set of all delivery locations. Finally, let $\mathcal{G} = \{1, 2, \dots, M\}$ uniquely index the delivery locations in \mathcal{D} , i.e., there exists a bijective mapping

$$m : \mathcal{D} \rightarrow \mathcal{G}. \quad (1)$$

To formulate our delivery service problem, we first partition the delivery locations into, at most, N disjoint sets that the vehicles can be assigned to. We achieve this by defining an assignment matrix.

Definition 3. The assignment matrix, \mathbf{A} , is an $N \times M$ binary matrix, where element $a_{ij} \in \{0, 1\}$ is 1 if vehicle $i \in \mathcal{N}$ is assigned to deliver a package to delivery location $j \in \mathcal{G}$ and 0 otherwise.

The objective of our delivery service is to determine the number of vehicles to send on deliveries such that operating cost and customer satisfaction are jointly optimized. We model customer satisfaction as being inversely proportional to package delivery time, with the cost denoted by J_s , and we denote the total travel cost by J_c , which is proportional to the total round-trip time of all vehicles, i.e.,

$$J_s(\mathbf{A}) = \sum_{j \in \mathcal{G}} \frac{t_j(\mathbf{A})}{M}, \quad (2)$$

$$J_c(\mathbf{A}) = \sum_{i \in \mathcal{N}} T_i(\mathbf{A}), \quad (3)$$

where t_j denotes the time taken for package $j \in \mathcal{G}$ to be delivered, and $T_i \in \mathbb{R}_{\geq 0}$ is the round-trip travel time for vehicle i to make its deliveries and return to the depot. Note that both T_i and t_j depend on the actual route taken by the vehicles, which is a function of the assignment matrix, \mathbf{A} . We determine the assignment matrix, and thus the optimal number of vehicles to deploy, by solving the following centralized assignment problem.

Problem 1 (Delivery Assignment). Assign vehicles to deliver packages such that the average delivery time and round-trip travel time are jointly minimized,

$$\min_{\mathbf{A}} \left\{ \alpha J_s(\mathbf{A}) + (1 - \alpha) J_c(\mathbf{A}) \right\} \quad (4)$$

subject to:

$$\sum_{i \in \mathcal{N}} a_{ij} = 1 \text{ for all } j \in \mathcal{G},$$

$$a_{ij} \in \{0, 1\} \text{ for all } i \in \mathcal{N}, j \in \mathcal{G},$$

where $0 \leq \alpha \leq 1$ is an intrinsic parameter that balances the tradeoff between minimizing operating cost and maximizing customer satisfaction for a particular delivery service, and a_{ij} , $i \in \mathcal{N}$, $j \in \mathcal{G}$, are the elements of the assignment matrix \mathbf{A} . Note that the first constraint ensures that each package gets delivered only by one vehicle, and some vehicles may not be assigned to deliver any packages.

In order to deliver the packages and therefore compute the cost components of Problem 1, we need to determine the route taken by each vehicle given the assignment matrix, \mathbf{A} . We define the delivery route of vehicle $i \in \mathcal{N}$ as the sequence $\mathcal{S}_i := (s_1, s_2, \dots, s_n)$, where $n = \sum_{j \in \mathcal{G}} a_{ij}$ (Definition 3) and $\bigcup_{k \in \{1, \dots, n\}} s_k = \{v \in \mathcal{D} \mid j = m(v), a_{ij} = 1\}$, where m maps delivery locations to indices by (1). To determine the optimal sequence to deliver their assigned packages, each vehicle i solves the following problem.

Problem 2. For each vehicle $i \in \mathcal{N}$, with a given delivery assignment matrix \mathbf{A} , determine the path \mathcal{P}_i that minimizes the total travel time such that the vehicle starts and ends at the depot and delivers all assigned packages, i.e.,

$$\min_{\mathcal{P}_i, \mathcal{S}_i} T_i \quad (5)$$

subject to:

$$p_1 = d, \quad p_1 \in \mathcal{P}_i,$$

$$p_\ell = d, \quad \ell = |\mathcal{P}_i|, p_\ell \in \mathcal{P}_i,$$

$$\mathcal{S}_i \text{ is a subsequence of } \mathcal{P}_i,$$

where $\mathcal{P}_i = (p_1, p_2, \dots, p_\ell)$ is the path taken by vehicle i (Definition 2), $\mathcal{S}_i = (s_1, s_2, \dots, s_n)$ defines the sequence of deliveries, and $d \in \mathcal{V}$ is the node corresponding to the depot entrance.

Thus, the cost of the optimal assignment in Problem 1 is determined by each vehicle's solution to Problem 2, which is equivalent to the TSP. In the following section, we detail our scalable solution to solve Problems 1 and 2 in simulation,

and we verify this solution experimentally. To this end, we impose the following assumptions.

Assumption 1. The delivery vehicles are equipped with connected and automated vehicle technologies that significantly reduces the effects of traffic bottlenecks and delays [25], [26].

Assumption 2. The speed limits on the road network are fixed and known a priori.

Assumptions 1 and 2 ensure that the environment is deterministic when the vehicles plan their routes. These assumptions can be relaxed by including a time-varying term to the edge cost to account for traffic lights, stop signs, and congestion. Assumption 1 can also be relaxed by allowing different delivery modes that bypass congestion, e.g., motorcycle, bicycle, and drone delivery. In the case that Assumption 2 is relaxed, and the traffic information is stochastic, a data-driven approach could be used to calculate the expected delay at each edge.

Assumption 3. The vehicles have sufficient energy to achieve their assigned delivery routes.

Assumption 4. The delivery locations are fixed and known a priori and without constraints on the delivery time.

Assumptions 3 and 4 ensure that any vehicle can be assigned to any sequence of deliveries, and that a solution is always guaranteed to exist to Problem 1. Assumption 3 can be relaxed by including a total energy cost constraint in Problem 2 and discarding any assignments that impose infeasible delivery routes. Assumption 4 is relevant for last-mile delivery, where the delivery service knows what packages must be shipped out before they arrive. This assumption can be relaxed by adding a delivery time constraint to Problem 2 and discarding any assignments that don't satisfy the delivery constraints. If either assumption is relaxed, then it is necessary to derive conditions for the existence of a feasible assignment matrix.

IV. SOLUTION APPROACH

In this section, we describe a scalable method of assigning vehicles to packages, and determining their delivery routes, in order to minimize the joint travel and delivery time costs. In Problem 1, the parameter α describes the structure of a particular company and how the cost of vehicle usage and labor is weighed against the benefits of faster delivery times. A higher α implies that $J_s(\mathbf{A})$ is the dominant term, and this will result in solutions that use more vehicles to decrease average delivery time. In contrast, a small value of α implies that $J_c(\mathbf{A})$ dominates, and this will result in fewer delivery vehicles being assigned to reduce the total amount of time spent traveling across all vehicles.

First, our delivery service receives the number of packages, M , and their delivery locations. To solve the assignment of vehicles to packages (Problem 1), we employ complete-linkage clustering [27]. While complete-linkage

clustering may not always yield the optimal solution to Problem 1, it is a hierarchical clustering algorithm. Therefore, it is able to generate an approximately optimal assignment of vehicles to packages for every case simultaneously, i.e., assignments for using $1, 2, \dots, N$ vehicles, in $O(n^2)$. Complete-linkage clustering also ensures that the maximum distance between any two packages in the same cluster is minimized. In contrast, to find the optimal assignment, the Hungarian Algorithm has a computational complexity of $O(n^3)$ for a single scenario, i.e., a fixed number of participating vehicles. This requires significantly more evaluations of Problem 2; thus we selected the complete-linkage clustering algorithm to ensure scalability.

In complete-linkage clustering, the M delivery locations are first clustered into M groups, i.e., each delivery assignment is a singleton. This corresponds to the M leaf nodes in our hierarchical clustering tree. Next, the two packages with the shortest separating distance are combined, resulting in $M - 1$ groups of packages, which adds a branch to our hierarchical clustering tree. This process is repeated until only a single group, containing all M packages, remains; this corresponds to the root node of our hierarchical clustering tree. Finally, we start at the root node and travel along the hierarchical clustering tree to determine the assignment of $1, 2, \dots, N$ vehicles to the M packages. Thus, we can enumerate all of the resulting $1, 2, \dots, N$ assignments to determine which one minimizes the total cost.

Problem 2 is a modified TSP, which contains additional nodes that are not associated with a package delivery. These problems are known to be NP-hard, with a computational cost approaching $O(n!)$. Thus, to ensure our approach scales with a large number of vehicles, we solve Problem 2 using a greedy search algorithm. Each vehicle $i \in \mathcal{N}$ begins at the depot, and it calculates the shortest path from its current location to each of its assigned delivery locations. The vehicle selects the nearest delivery location as the first element of its delivery sequence \mathcal{S}_i , and the second element is selected by comparing the distance of all remaining packages to $s_1 \in \mathcal{S}_i$. This process is repeated until \mathcal{S}_i contains all delivery locations exactly once, and this also yields the path \mathcal{P}_i taken by the vehicle. In the case of ties, the package with the lower index is arbitrarily selected. To demonstrate the scalability of our approach, we compared the computational time required to find a TSP solution by brute force with our greedy algorithm. Specifically, we randomly generated 50 scenarios for different numbers of packages, from $M = 4, 5, \dots, 20$. Due to the computational cost of TSP, we only computed its solution for up to 9 packages, and the performance of both approaches is demonstrated in Fig. 1. Note that the poor performance of the TSP necessitates a log scale on the computational time axis, and this shows the significant computational benefit of using the greedy search algorithm as the number of packages increases. Even for a small number of packages, the TSP solution quickly becomes intractable. This necessitates sacrificing some optimality to guarantee the scalability of our solution.

We also conducted 50 simulations where the package

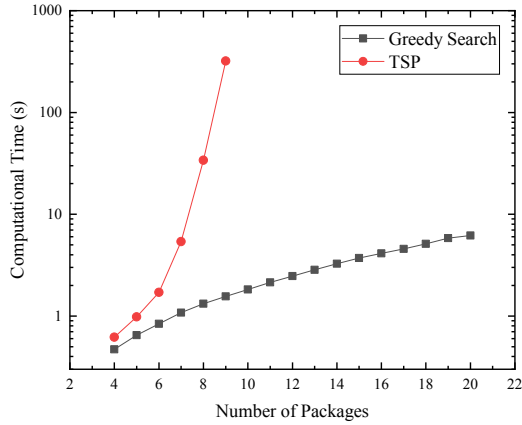


Fig. 1. Computational cost between the TSP and greedy search approaches for $N = 1$ vehicle. The computational time is plotted in a log scale due to computational complexity of TSP.

locations were determined randomly for $M = 3, 4, 5, 6$ packages. Fig. 2 quantifies the optimality gap of our greedy approach compared to TSP, and shows the percent increase in total travel time compared to the TSP solution. For low numbers of vehicles, the median time lost is less than 10%, however, Fig. 2 does demonstrate a consistent growth in the optimality gap. This gap is less relevant as the number of packages increases, since TSP quickly becomes intractable.

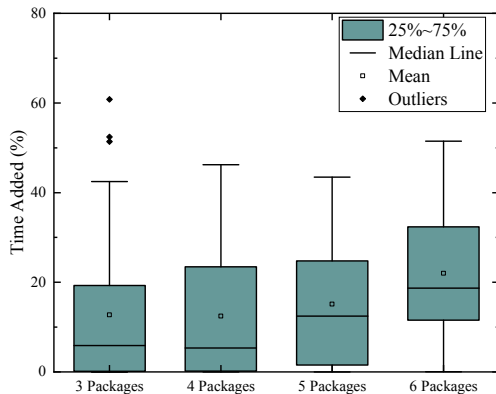


Fig. 2. The extra time spent by vehicles to complete their route using the greedy search instead of the TSP solution.

V. SIMULATION AND EXPERIMENT

To demonstrate the effectiveness of our approach, we performed a series of simulations based on the urban network present in the Information and Decision Science Lab's Scaled Smart City (IDS³C)¹. The IDS³C is a 1:25 scaled testbed spanning over 400 square feet, and it is capable of replicating real-world traffic scenarios using up to 50 ground and 10 aerial vehicles; for an overview of the IDS³C and its capabilities see [28]. IDS³C's road network consists of straight lines and arc segments. To implement our algorithm, we first constructed a graph to represent the IDS³C's road network

¹<https://www.youtube.com/watch?v=4x1i3oODn7Q>

using network analysis library NetworkX² in Python 3.7. We constructed the graph's nodes by computing the start and end points of each road segment. To eliminate redundant nodes, which were generated due to rounding errors, we combined any two points that were separated by one lane width or less. The resulting graph of IDS³C consists of 149 nodes and 220 edges, and is displayed over a diagram of the IDS³C in Fig. 3. For each edge in the graph, we defined the cost as the length of the road segment divided by its speed limit. We considered a speed limit of 50 km/h for straight roads and 25 km/h for arc segments. Fig. 3 also shows the node corresponding to the depot (blue) and six package locations (orange) that we used in the physical experiment, which we discuss in the following section.

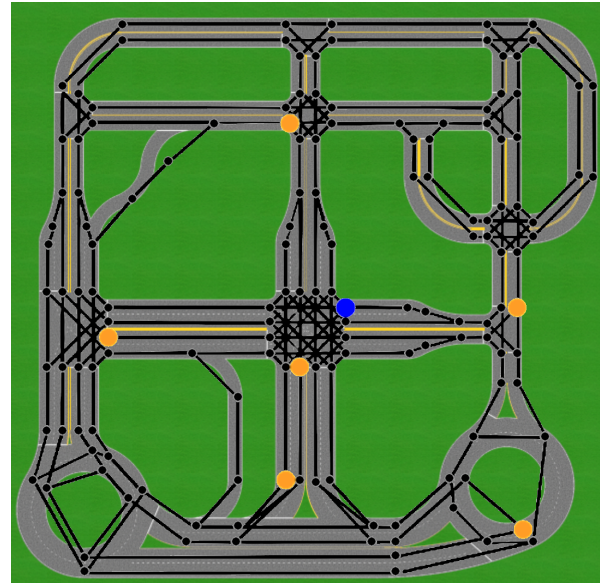


Fig. 3. The depot (blue) and package locations (orange) for the 6 package simulation.

A. Simulation Results

To simulate our last-mile delivery service, a user inputs the number of packages, M , and their corresponding delivery locations. We allow any node except the depot to be a delivery location, as the depot is a fixed node that corresponds to the initial and final destination of all vehicles. Next, we apply complete-linkage clustering based on the position of each delivery location in \mathbb{R}^2 using Scikit-Learn's agglomerative hierarchical clustering package³. The clustering yields the assignment matrix for every possible number of vehicles. Then, we iterate through the hierarchy of $1, 2, \dots, N$ clusters and determine the greedy path taken by each vehicle using NetworkX's A* path finding package². We used the default setting of no heuristic, thus our solution is equivalent to Dijkstra's algorithm. Finally, we evaluate the N costs, corresponding to the $1, 2, \dots, N$ vehicles, and select the optimal number of vehicles such that the total cost

²NetworkX website: <https://networkx.org>

³Scikit-Learn website: <https://scikit-learn.org/stable/>

is minimized for a given value of α . We compute the cost from the total travel time and average delivery time, which correspond to the sum of all edge weights along a vehicle's path and the sum of all edge weights from the origin to the first instant that a vehicle reaches one of its assigned delivery nodes, respectively. Algorithm 1 shows our pseudocode.

Algorithm 1: Generate delivery routes for all possible number of vehicles.

Input: Delivery locations of M Packages, Number of available vehicles N

```

numVehicles  $\leftarrow 0$  ;
while numVehicles  $\leq N$  do
    Group packages into numVehicles clusters;
    Assign all packages in each cluster to a vehicle;
    for each vehicle do
        while unvisited assigned packages  $> 0$  do
            Calculate cost of paths to each assigned package delivery point;
            Add lowest cost path to the vehicle's path;
        end
    end
    numVehicles  $\leftarrow$  numVehicles + 1 ;
end

```

To analyze the performance of our last-mile delivery service, we performed 30 simulations by randomly initializing $M = 6$ delivery locations on the network. The cost components, i.e., total travel time and average delivery time, are presented in Figs. 4 and 5, respectively. As expected for one depot in the network, Fig. 4 shows that total travel time increases with the number of vehicles, while Fig. 5 demonstrates that the average delivery time decreases as the number of vehicles increases. These competing objectives present a trade-off between the cost of delivering packages and customer satisfaction.

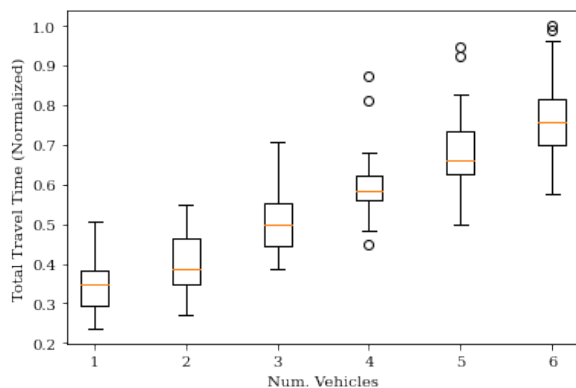


Fig. 4. The total time spent by vehicles to complete their route, from 30 tests with 6 packages.

B. Experimental Results

To validate our simulated solution for the optimal number of vehicles, we performed a small-scale experiment in the

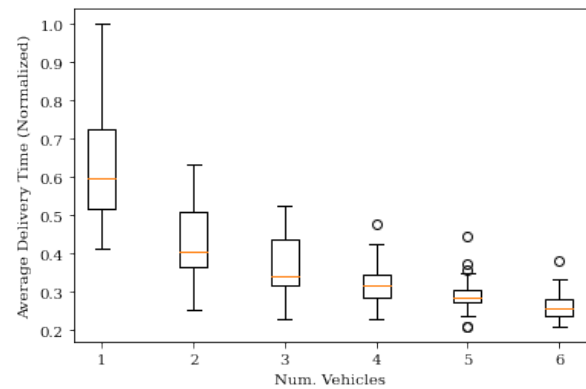


Fig. 5. The average delivery time of each package, from 30 tests with 6 packages.

IDS³C using the $M = 6$ package locations presented in Fig. 3. While the number of packages was limited by the space available in the city, we expect the results to scale with Fig. 1 for a larger city—both in terms of networks size and number of packages. We applied Algorithm 1 to solve Problems 1 and 2, and used the resulting paths as input for the vehicles in the IDS³C. Finally, relaxing Assumption 1, we determined the control input of each vehicle $i \in \mathcal{N}$ using the Intelligent Driver Model with standard parameters [29]. In addition, the vehicles each stop for 3 seconds at each delivery node along their route.

We performed six experiments, one for each number of vehicles, and computed the customer satisfaction cost (2) and total travel time (3) for each case. In order to compare the simulation and experimental results, we normalized the resulting costs by their maximum value, i.e., we divided each component of the cost by the maximum value that it took in all cases. The resulting comparison is presented in Fig. 6 for $\alpha = 0.5$. This shows that while the cost of the simulation and experiment differs by at most 10%, the simulation correctly predicts $N = 3$ as the optimal number of vehicles for this particular scenario. The simulation consistently under-predicts the total cost of the experiment for $N < 6$, and this is due to the fact that each vehicle stops for 3 seconds to make a delivery, which increases both the total travel time and subsequent delivery times. Another reason for this discrepancy is that the simulation considers the constant speed over the trip, while the vehicle's speed in the experiment varies to make deliveries. Additionally, the vehicles may need to adjust their speed in the experiment to satisfy the safety constraint with other vehicles in the network. In cases where $N = 1, 2, 3$, a single vehicle delivers at least 3 packages, and this results in an average increase of 3 seconds (10%) per package for that vehicle. Similarly, when $N = 5$, the vehicle that delivers 2 packages is also assigned to the longest path, which further increases the delivery time. Finally, for $N = 4$, the packages are distributed more evenly between all available vehicles, and in the 6 vehicle case, the delay caused by delivering packages does not affect customer satisfaction. Experimental results and other supplementary material are available on the paper's

website: <https://sites.google.com/view/ud-ids-lab/lmds>.

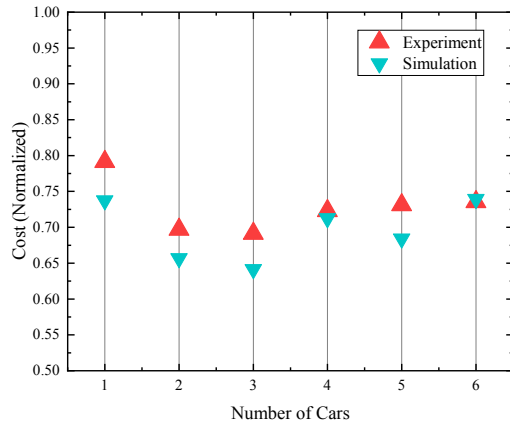


Fig. 6. The simulated and actual cost incurred for different numbers of vehicles in the 6 package delivery scenario with $\alpha = 0.5$.

VI. CONCLUSION

In this paper, we proposed and experimentally validated a heuristic clustering and greedy search algorithm to solve the last-mile delivery problem. Our approach trades optimality for computational tractability, and we quantified the optimality gap in our approach through random sampling. Finally, we demonstrated the performance of our delivery service in a scaled testbed using 6 different experiments. Future work includes capturing the effect of delays and disturbances in the testbed and simulation, embedding total energy and delivery time constraints in the path generation problem, and enhancing our clustering approach to account for the underlying directed graph that represents the transportation network. Including constraints on the number of packages per vehicle and handling vehicle failure is another interesting direction of future work.

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