HYBRID SIMULATION-OPTIMIZATION MODEL TO DESIGN AUTONOMOUS DELIVERY VEHICLES NETWORKS

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ABSTRACT

This paper proposes a novel integration of simulation, machine learning and mathematical optimization to design a delivery network of autonomous delivery vehicles (ADVs). To obtain the desired scalability, the model is pre-solved using k-means clustering to batch orders based on proximity, then Capacitated Vehicle Routing Problem (CVRP) and Facility Location (FL) models are used to minimize the ADVs' total traveled distance. The model considers concepts to handle a semi-connected network and use of modular dispenser. Simulation modeling was used to address stochasticity caused by teleoperators required in the process and help identify the resources required for various volume scenarios. A case study is presented where the objective is to optimize the number of ADVs required and teleoperators' utilization given a stochastic demand.

Keywords: Autonomous Delivery Vehicles, Two-Echelon Delivery Network, Machine Learning, Optimization.

1 INTRODUCTION

Recent literature in transportation has focused on ADVs, as a promising mean to support parcel delivery. Given the increasing demand for optimizing last-mile delivery systems, researchers have explored the potential of ADVs as an efficient transportation method that is able to decrease labor expenses in comparison to conventional delivery vehicles [1]. In addition, it presents an environmentally friendly delivery alternative. ADVs can travel on congested roads without significant delay by using sidewalks. ADVs, also referred to as delivery robots, have the potential to reduce urban emissions for the last-mile delivery to customers as ADVs are powered by batteries [2]. However, there are several inherent limitations to the successful use of ADVs, such as the low speed, limited capacity, and limited accessibility [3]. The ADV concept evaluated in this paper is considered an autonomous driven vehicle. Human teleoperators are particularly needed for supervision during road crossings and when encountering unforeseen occurrences (e.g. trash bins in the way or road works). Moreover, due to their reliance on batteries, ADVs are likely to have a limited range compared to conventional fuel-based delivery vehicles. Currently, conventional vehicles perform the majority of urban logistical activities. However, their long-range delivery and large-volume gas consumption present an actual challenge for such vehicles. Therefore, a combination of conventional vehicles and ADVs delivery has been proposed in several transportation research studies [4], called two-echelon vehicle routing. While offering new opportunities, the use of ADVs in last mile deliveries is subject to different constraints as compared to regular delivery vehicles. Therefore, their use will require the application of new optimization techniques to ensure their efficiency and sustainability [5].

Proc. of the 2024 Annual Simulation Conference (ANNSIM'24), May 20-23, 2024, American University, DC, USA
P.J. Giabbanelli, I. David, C. Ruiz-Martin, B. Oakes and R. Cárdenas, eds.

In this work, the authors are proposing an optimization algorithm that is integrated into a simulation model to enable a rolling next day delivery system (e.g. orders planning occurs on Monday for Tuesday deliveries). The paper is structured as follows: Section 2 explains relevant works, Section 3 provides a description of the experimentations conducted to test the optimization model, Section 4 provides a simulation case study, and Section 5 explains the conclusion and future works.

2 RELEVANT WORKS

Last mile delivery optimization is a growing field of interest in research due to its pivotal role in mitigating delivery costs, primarily attributed to the significant inefficiencies inherent in delivery networks [6]. Several challenges confront last-mile delivery optimization, including traffic congestion, urbanization, and heightened customer expectations for swift delivery [7]. Previous research, shows that ADV optimization reduces labor costs, delivery time, and provides a higher predictable delivery times, despite their significant cost investments required [8, 9, 10]. Previous research related to ADV routing problem has addressed several methodologies. The use of Genetic along with k-means clustering to solve an ADV multi-echelon problem was addressed [2]. Multi-vehicle truck-and-robot routing problem was proposed [11]. Particle swarm algorithm, along with an Dijkstra algorithm were used to optimize a fleet of ADV vehicles [12]. The authors propose the use of simulation modeling for results validation. A recent study [13] tackles the problem of charging ADVs by optimizing the distribution of power systems across the delivery network. ADV route optimization should also consider charging schedules, uncertain travel time, and uncertain service time [14]. Hybrid simulation-optimization has been recently addressed as an effective way to address stochasticity in such networks [15]. Designing an ADVs network can be highly impacted by the selection of multi-depots or dynamic depots. Thus, approaches were suggested for dynamic depot selection [16]. The optimization of fleet size under dynamic demand has been recently addressed using mixed integer programming [17, 18].

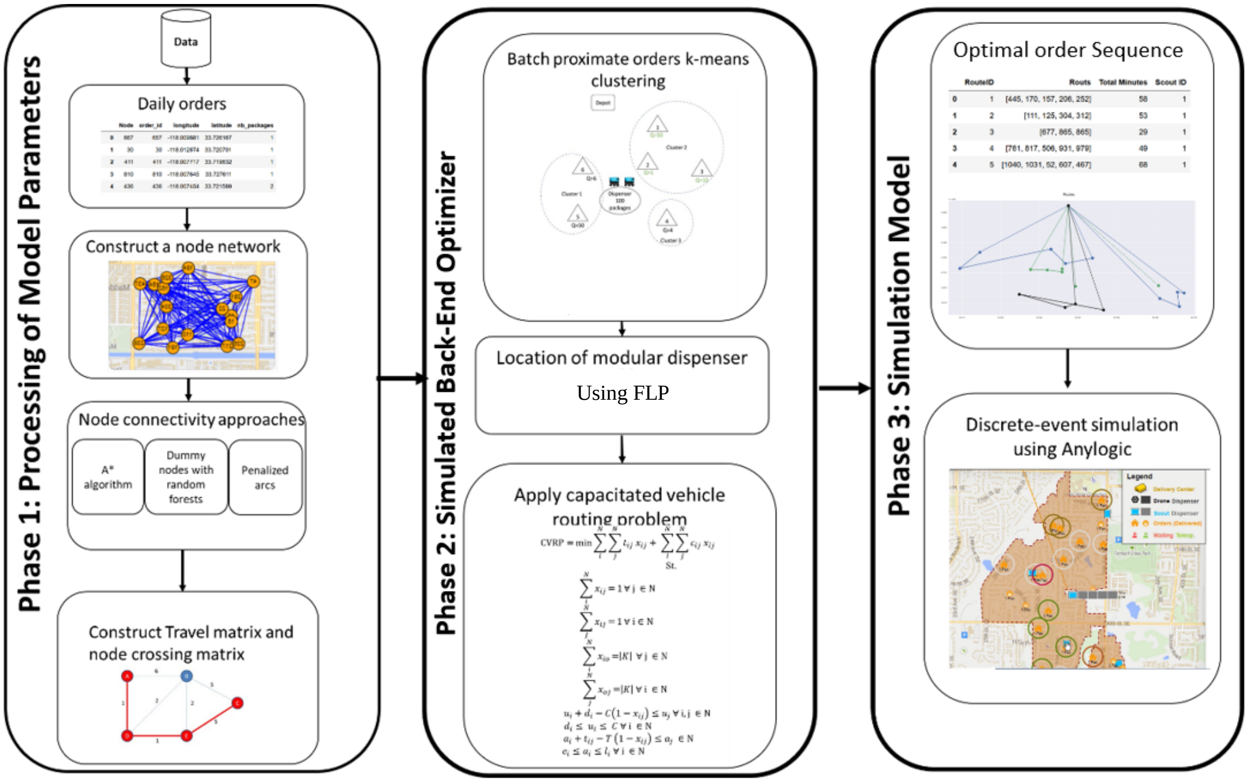
Previous research studies have focused on the modeling of a two-echelon ADVs network, with a primary focus on routing optimization. None of the proposed approaches have investigated the specific impact of integrating teleoperator involvement in ADV deliveries. In this work, teleoperators are required to take control of the ADVs while they run on sidewalks and to unload packages at the customers' doors. This research, is inspired by the two-echelon optimization model proposed by [2], while focusing on the optimization of the ADVs second echelon network with teleoperator considerations. The objective of this optimization is to make the best use of ADVs and therefore reduce overall costs of the delivery network. In this study, the first echelon consists of a depot (a modular trailer) and its location. The second echelon represents the ADVs and their routing to the end customer. The contribution of this work is 1) proposing an integrated clustering, batching, routing and depot allocation algorithm tested with real-life data; 2) addressing operator involvement and charging considerations into the optimization problem using discrete event simulation modeling; 3) addressing approaches to handle node-connectivity for ADVs network; 4) showing how machine learning, optimization, and simulation modeling can be implemented to design an ADVs network using a real case study.

3 METHODOLOGY

In this section, we explain the proposed End-to-End model that converts a business objective of delivering 75 packages to customers into a scalable solution, despite encountering constraints related to data unavailability.

3.1 Proposed End-to-End Framework

The objective of this paper is to test the performance (utilization and throughput) and requirements (number of teleoperator and ADVs required) of a proposed delivery system. The data preprocessing phase includes defining a candidate delivery area for which forecasted demand and historical network data is available. Shortcomings were identified in network data availability in the selected delivery area since manual testing and data gathering is labor extensive. Approaches to build the network connectivity efficiently are suggested in this work. With the full network built, a routing model can be applied within a simulated environment. The simulation model generates random orders through delivery zones. These orders are batched on a daily basis to run the routing optimization model for the next day. The routing model clusters the orders based on their locations and then run an optimization model for routing and depot localization. Once the routing optimization model is solved, the proposed routes are simulated to test the approach robustness to variability (i.e., random teleoperator involvement and teleoperator tasks backlog). Figure 1 explains the proposed framework.



Daily orders

	Node	order_id	longitude	latitude	nb_packages
0	667	667	-118.009681	33.726187	1
1	30	30	-118.012874	33.726791	1
2	411	411	-118.007717	33.719832	1
3	810	810	-118.007845	33.727611	1
4	436	436	-118.007454	33.721589	2

Optimal order Sequence

	RouteID	Routs	Total Minutes	Scout ID
0	1	[445, 170, 157, 206, 252]	58	1
1	2	[111, 125, 304, 312]	53	1
2	3	[677, 865, 865]	29	1
3	4	[761, 817, 506, 931, 979]	49	1
4	5	[1040, 1031, 52, 607, 467]	68	1

$$\text{CVRP} = \min \sum_i^N \sum_j^N t_{ij}\, x_{ij} + \sum_i^N \sum_j^N c_{ij}\, x_{ij}$$

St.

$$\sum_i^N x_{ij} = 1 \; \forall \, j \in \text{N}$$

$$\sum_j^N x_{ij} = 1 \; \forall \, i \in \text{N}$$

$$\sum_i^N x_{io} = |K| \; \forall \, j \in \text{N}$$

$$\sum_j^N x_{oj} = |K| \; \forall \, i \in \text{N}$$

$$u_i + d_i - C(1 - x_{ij}) \le u_j \; \forall \, i, j \in \text{N}$$

$$d_i \le u_i \le C \; \forall \, i \in \text{N}$$

$$a_i + t_{ij} - T(1 - x_{ij}) \le a_j \in \text{N}$$

$$e_i \le a_i \le l_i \; \forall \, i \in \text{N}$$

Figure 1: Hybrid simulation-optimization approach for ADVs delivery optimization.

3.2 Optimization Model

The set N ∈ $\{1, .. n\}$ contains all customer order locations in a predefined geographical area for the next day. First, k-means clustering is applied to sub-divide the NP-hard routing problem into smaller regions. Let x_i be the latitude and longitude of a customer order, the approach is to assign each location to a cluster centroid c_j using (1)

$$\arg\min \sum_i \sum_j \left| x_i - c_j \right|^2. \tag{1}$$

The next step, is to apply Capacitated Vehicle Routing Problem (CVRP) for each cluster to sequence the ADVs movement and reduce the traveling distance. The model formulation of the capacitated vehicle routing is shown in the Equations below:

Objective Function (CVRP):

$$\text{CVRP} = \min\left(\sum_i \sum_j t_{ij}\, x_{ij} + \sum_i \sum_j c_{ij}\, x_{ij}\right). \tag{2}$$

Subject to:

$$\sum_i x_{ij} = 1 \ \forall \ \mathrm{j} \ \in \mathrm{N}, \tag{3}$$

$$\sum_j x_{ij} = 1 \ \forall \ \mathrm{i} \in \mathrm{N}, \tag{4}$$

$$\sum_i x_{ij} = |K| \ \forall \ \mathrm{j} \ \in \mathrm{N}, \tag{5}$$

$$\sum_j x_{ij} = |K| \ \forall \ \mathrm{i} \ \in \mathrm{N}, \tag{6}$$

$$u_i + d_i - C\left(1 - x_{ij}\right) \leq u_j \ \forall \ \mathrm{i,j} \ \in \mathrm{N}, \tag{7}$$

$$d_i \leq \ u_i \leq \ C \ \forall \ \mathrm{i} \ \in \mathrm{N}, \tag{8}$$

$$a_i + t_{ij} - T\left(1 - x_{ij}\right) \leq a_j \ \forall \ \mathrm{i,j} \ \in \mathrm{N}, \tag{9}$$

$$e_i \leq a_i \leq l_i \ \forall \ \mathrm{i} \ \in \mathrm{N}. \tag{10}$$

The integration of k-means clustering and CVRP is inspired by Dan et al [2]. The CVRP problem is explained as follows: Let c_{ij} be the distance between any two locations i and j, the variable x_{ij} denotes that there is a route between the two locations i and j, the variable u_i is used for connectivity and d_i is demand per location i. a_i is the arrival time at point i, t_{ij} represents the traveling time between locations i and j. e_i and l_i are variable time window values ensuring we are delivering the orders on the same day. T is a large number. A fleet of homogenous ADVs exists in list K. The objective function minimizes the total traveled time and road crossing time (constraint 2). Constraints 3-4 guarantee that every location is visited only once during the route. Constraints 5-6 introduce the number of vehicles used. Constraint 7 eliminates sub tours. Constraint 8 respects the demand of every ADV. Note that C is the maximum capacity of the ADVs and should not be violated per route. Constraints 9-10 are used to sequence the visits based on the maximum travel time per vehicle. To solve the proposed model, Google-OR solver was used considering its quick running time. The existing model, assumes that a depot has a fixed location. However, this option may not be feasible since the ADVs concept evaluated has a low speed and may take a long time to travel from the depot to the first location in a route. The k-means clustering, however, would prevent the case that ADVs would travel to a very long location. In this work, we propose the use of a modular trailer that can carry ADVs and travels to an optimal location for each k-means cluster of customer orders.

To decide the optimal location of the modular trailer, we use a simplified version of facility layout problem (FLP), based on the one proposed by Gourbi Optimization [19]. Let $i \in I$ be index and set of customer locations, $j \in J$ be index and set of candidate trailer locations (or facility) locations, d_{ij} is the distance between facility j and customer i The variable $select_j \in \{0,1\}$ equals to 1 if we place the trailer at candidate location j; and is 0 otherwise. The variable $assign_{ij} \in [0,1]$ is a non-negative continuous variable determines the fraction of supply received by customer i from facility j. The objective function 11 minimizes the total distance. Constraint 12 makes sure that each customer's demand is fulfilled. Constraint 13 connects the trailer location to demand points. The model was used as an agent in the simulation software, and is solved on Gurobi Optimization solver each day.

Objective Function (Z):

$$min \ Z = \sum_j \ \mathrm{select_j} + \sum_j \sum_i \ d_{ij}.\mathrm{assign_{ij}}. \tag{11}$$

Subject to:

$$\sum_j assign_{ij} = 1 \ \forall \ \mathrm{i} \ \forall \ \mathrm{j}\,, \tag{12}$$

$$assign_{i,j} \leq select_j \forall i. \tag{13}$$

3.3 Handling of Non-Connected Network

ADVs use road crossings and custom travel distances when traveling across blocks. This research, uses manually gathered data of distance between any two locations and number of crossings. However, as a limitation of existing data, the network is not fully connected since ADVs currently cannot cross highways, and ADV road crossings are not available in all streets. These current operational constraints cause unreachable delivery zones or disconnected routes. Figure 2 shows an example of connected delivery zones in orange and disconnected delivery zones highlighted in red.

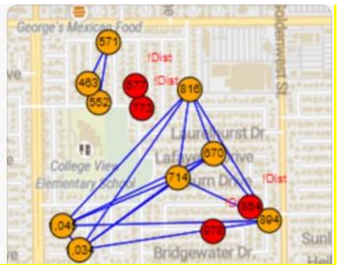


Figure 2: Isolated delivery zones and non-connected network.

This section, looks into ways to construct a travel matrix that can be used to connect all of the areas to build ADVs' routes with more ADVs road crossings. This most accurately describes the desired state for the practical assessment described in this paper.

3.3.1 Penalized Approach

In this approach, we assume a subset of penalized arcs linking disconnected destinations. These arcs are implemented between locations i and j if we expect crossings to be realizable in the future and they will be penalized if they are used by the routing algorithm. This approach is simple and can provide high scalability since it does not assume changes to existing data. Although, it may lead to inaccuracies in the number of required ADVs due to assumptions made on the penalty.

3.3.2 Use of Random Forests and dummy nodes at cross sections

The approach, requires adding dummy nodes at the main highways and basic intersections. More precisely, for an intersection isolating two delivery zones, one node is added in each delivery zone and we build an arc between those nodes thus creating a virtual road crossing representing the desired future state. From there, the travel distance between locations i and j can be estimated using the shortest path (explored in section 3.3.3) between any two locations or a predictor. In this approach, we explore random forest regression [20] predictor to determine the number of crossings between two locations and the total route duration if there is no data provided in a semi-connected network. This machine learning model was trained using historical data of latitude, longitude, and distance between two locations using haversine. This approach is simple and can provide high scalability, though it may lack flexibility and accuracy in an operational context.

3.3.3 Detailed Network Optimization using A* navigator

This approach also uses dummy nodes to connect isolated delivery zones and defines the routing duration using shortest path through an A* navigator. Flexsim [21] Simulation software was used for its A* navigator implementation. The full scaled network was built in this digital environment. At each street, road crossings were added to allow the ADVs to cross the street. The simulation runs for all possible travel arcs to generate a matrix showing the distances and number of road crossings between each possible combination of delivery zones while also offering the flexibility to disable/enable/penalize some paths. The routes can be activated programmatically in combination with Flexsim integrated optimizer to define the exact location of the most optimal routes to use. Figure 3 partially demonstrates the digital representation of the objects used in the Flexsim model. This method requires some configuration for each delivery area observed impacting its scalability, though it is the most realistic and flexible solution to define the optimal route durations for a desired future state.

Figure 3: Flexsim network using A* navigator.

3.4 Routing Model Integration with Simulation Model

A Discrete-Event Simulation model was built using Anylogic [22]. This model was used to address stochasticity and better represent real life constraints. The routing optimization model feeds a set of routes to be fulfilled to the Simulation model which allows the users to test if these routes can be realized in time with a predefined number of teleoperators. The dynamic and stochastic effects which could not have been considered in the route sequencing model includes teleoperator tasks generation and queuing. The teleoperators are randomly required to take control of the ADVs while they run on sidewalks. Teleoperators are also required when the ADVs unload packages at the customers' door and when ADVs need to cross roads. The Simulation model provides a validation for the number of ADVs required, their average packages delivered per hour, the number of simultaneous tasks teleoperators will handle and the teleoperators' utilization. Figure 4 shows a visual representation of the Simulation model where the circles are a color-coded representation of the assigned clusters in the optimization phase.

Figure 4: Simulation model showing demand clusters and teleoperators' tasks queuing.

4 EXPERIMENTATIONS

In this section, we provide experiments to test the proposed model.

4.1 Testing Node Connectivity Approaches

Demand would not be met for delivery areas if connectivity is not maintained since some delivery areas could not be reached. Several methods were proposed to achieve node connectivity, these methods were compared using the number of ADVs required to fulfill all orders using the hybrid simulation-optimization framework presented in Figure 1. Figure 5, shows that A* and Penalized approaches are similar in majority of tested volume scenarios when assessing the number of ADVs required to fulfill all orders. The connected network using dummy node read to a lower number of required ADVs by 1 – 2. In this research, we will employ the A* approach for further experiments, owing to its flexibility and conservativeness.

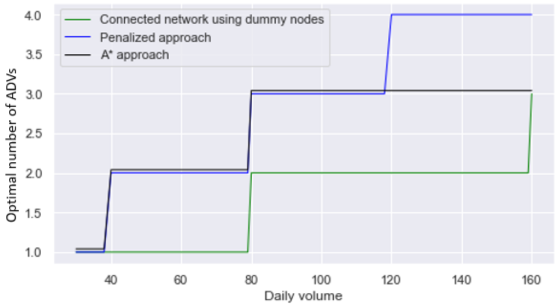


Figure 5: Number of ADVs needed per volume scenario for different node connectivity approaches.

4.2 Use of Modular Dispenser

This Optimization experiment shows that using FLP to determine the location of a modular trailer can improve ADVs' average utilization by 39%. Table 1 and Figure 6 shows variations on ADVs' utilization for a range of delivery volumes and depot locations.

Table 1: Use of modular dispenser.

Optimization run	**Volume**	**ADVs' utilization [%] using**		**Improvement in ADVs' utilization due to dynamic dispenser [%]**
		Fixed dispenser	**Dynamic dispenser (FLP)**	
1	40	63	42	21
2	45	46	46	0
3	50	76	54	22
4	55	89	62	27
5	60	90	51	39

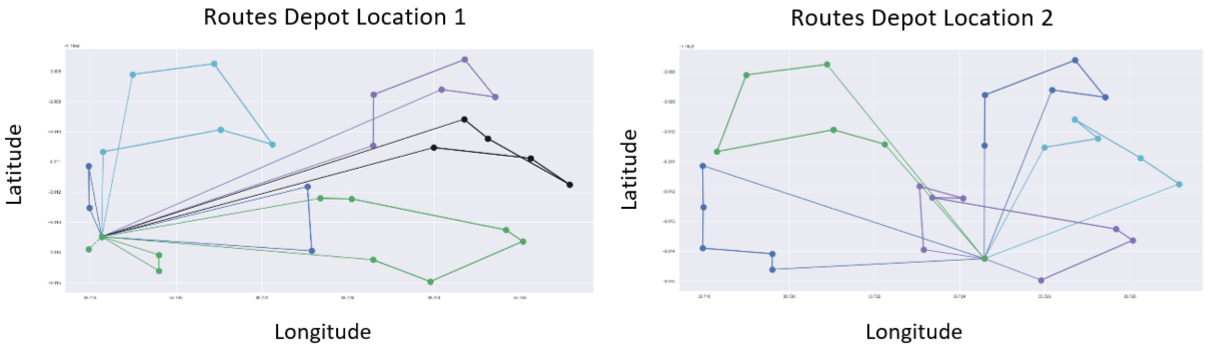


Figure 6: Routes representation for different depot location.

4.3 Addressing Stochasticity Using Simulation

Running the routing optimization model within the simulation model allows assessing accurately the impact of the random teleoperator involvements and their compounding effects to make sure the proposed solution is robust against variability. In absence of historical data, the use of empirical distributions mixed with educated guesses allowed modeling the teleoperators' random tasks and durations as follow; road crossings are distributed uniformly between the start and the end of a travel route, every road crossing will require a teleoperator with a triangular distribution between 36-54 seconds, the ADVs traveling on sidewalks will require a teleoperator to remediate at random times which follow a normal distribution with a mean of 60 sec and a standard deviation of 6 sec, the encounter's duration follows a triangular distribution between 10-14 sec and once the ADVs have reached their destination, it will require a teleoperator to unload the package for a duration following a triangular distribution between 36-54 sec. The simulation model was ran using an assumed average of 75 packages per day for a broad range of hypothetical inputs combination to test the solution's performance. The inputs varied were the ADVs' speed and capacity, the optimal and sub-optimal dispenser's location and the number of teleoperators. Moreover, the number of clusters was varied to measure the impact it has on the system's performance. All these scenarios run allowed assessing how the system would perform under uncertainty. A sample of the results of these simulation runs are shown in Table 2.

Table 2: Simulation Model runs with different Inputs.

	Inputs					Outputs			
Run id	**ADVs' Speed (MPS)**	**dispenser location id**	**ADVs' capacity**	**Number of teleops.**	**Number of clusters**	**ADVs required**	**Packages per hour per ADV**	**Max. tasks teleop.**	**Teleops.' utilization**
1	0.8	1	8	2	2	2	4.71	2	23%
2	0.8	1	8	2	3	2	4.71	2	24%
3	0.8	1	8	3	2	2	4.71	2	15%
4	0.8	1	8	3	3	2	4.71	2	16%
5	0.8	1	10	2	2	2	4.71	2	21%
6	0.8	1	10	2	3	2	4.71	2	22%
7	0.8	1	10	3	2	2	4.71	2	14%
8	0.8	1	10	3	3	2	4.71	2	14%
9	0.8	2	8	2	2	3	3.14	3	29%
10	0.8	2	8	2	3	3	3.14	3	29%
11	0.8	2	8	3	2	3	3.14	3	19%
12	0.8	2	8	3	3	3	3.14	3	20%
13	0.8	2	10	2	2	2	4.71	2	25%
14	0.8	2	10	2	3	3	3.14	3	26%
15	0.8	2	10	3	2	2	4.71	2	17%
16	0.8	2	10	3	3	3	3.14	3	18%
17	0.9	1	8	2	2	2	4.71	2	22%
18	0.9	1	8	2	3	2	4.71	2	23%
19	0.9	1	8	3	2	2	4.71	2	15%
20	0.9	1	8	3	3	2	4.71	2	15%
21	0.9	1	10	2	2	2	4.71	2	20%
22	0.9	1	10	2	3	2	4.71	2	21%
23	0.9	1	10	3	2	2	4.71	2	13%
24	0.9	1	10	3	3	2	4.71	2	14%
25	0.9	2	8	2	2	3	3.14	3	27%
26	0.9	2	8	2	3	3	3.14	3	28%
27	0.9	2	8	3	2	3	3.14	3	18%
28	0.9	2	8	3	3	3	3.14	3	19%
29	0.9	2	10	2	2	2	4.71	2	24%
30	0.9	2	10	2	3	2	4.71	2	25%
31	0.9	2	10	3	2	2	4.71	2	16%
32	0.9	2	10	3	3	2	4.71	2	17%

Each of these simulation runs are averages based on 15 replications to ensure consistency of the results, produce an acceptable confidence interval in the number of ADVs required [23, 24, 25]. By using the binomial distribution with the number of ADVs required (2 or 3) allowed to identify that we are 95% confident that the proportion of experiments resulting in 2 ADVs required is between 64.60% and 72.90% and we are 95% confident that the proportion of experiments resulting in 3 resources required is between 27.10% and 35.40%. Those ranges fall within an acceptable confidence interval to ensure ADVs can deliver 75 packages per day for less than 4 ADVs. Moreover, teleoperators resources planning was eased since their requirements can be predicted in a parameterizable and risk-free environment.

Subject Matter experts used the provided results to drive design decisions regarding the ADVs' capacity. These Expert consultations allowed us to validate our predictions since their predicted number of ADVs required was between 2 and 4 based on their field experience, physical testing and static analysis. The teleoperators utilization has been validated against historical data where their utilization ranged from 16% to 25%.

The simulation model also allowed visually identifying opportunities to increase the delivery network performance by using orders scheduling algorithms and dynamic ADVs allocation among neighbor delivery areas.

5 CONCLUSION AND FUTURE WORK

This paper looked into a novel integration of simulation and optimization to design an ADVs delivery network that can be used by industries to advance autonomous delivery. The approach helps to design an ADVs network for unattended deliveries and provide its expected performance range for next day deliveries. The study showed that a hybrid simulation-optimization is needed to address stochasticity in ADVs deliveries caused by teleoperator disruptions. The model identified that 2-3 ADVs are able to deliver an average of 75 orders per day for a selected neighborhood. The model can help industries' ADVs planners determine the needed number of resources in an optimized delivery network. Some limitations of the current work identified were: The assumption made that the delivery network should be fully connected to represent the desired state whereas it could still be partially disconnected in the future, the use of empirical distributions mixed with educated guesses in absence of data for the simulation experiments and the lack of failure considerations (ADV breakdown, teleoperator unexpected unavailability, network issues, etc.). Whilst those considerations have been abstracted for the current research, the assessment of the framework performance has proven itself validated by comparing it with static analytics and expert consultation. Future work will apply factorial design to address more stochastic elements such as charging and demand distribution across neighborhoods, the possibility to integrate a hybrid vans-ADVs delivery model and ADVs dynamic allocation. Finally, this study showed that it is crucial to address operators' stochasticity when optimizing an ADVs delivery network in two-echelon vehicle routing problems to accurately assess the number of resources required.

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