Taxonomy of Shared Autonomous Vehicle Fleet Management
Problems to Inform Future Transportation Mobility

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Abstract

This paper presents a taxonomy to classify vehicle fleet management problems, across several dimensions, to inform future research on autonomous vehicle (AV) fleets. Modeling the AV fleet management problem will undoubtedly bring about new classes of vehicle routing, scheduling, and fleet management problems; nevertheless, the existing literature related to vehicle routing, scheduling, and fleet management provide a valuable foundation for future research on the AV fleet management problem. In this paper, we [1] classify the broadly defined AV fleet management problem using existing taxonomic categories in the literature; [2] add additional, or more nuanced, dimensions to existing taxonomic categories, and [3] present new taxonomic categories to classify specific AV fleet management problems. The broadly defined AV fleet management problem can be classified as a dynamic, multi-vehicle, pickup and delivery problem with explicit or implicit time-window constraints. We briefly review existing studies that fit into this class of fleet management problems. New taxonomy categories presented in this paper include fleet size elasticity, reservation structure, accept/reject decision-maker, reservation timeframe, ridesharing, vehicle repositioning, underlying network structure, and network congestion. Two goals of the taxonomy presented in this study are to provide researchers a valuable reference as they begin to model AV fleet management problems and to present novel AV fleet management problems to spur interest from researchers.

Keywords: Autonomous Vehicles, Autonomous Vehicle Fleets, Shared Autonomous Vehicles, Taxonomy, Fleet Management, Vehicle Routing Problem, Pickup and Delivery Problem, Shared Mobility
INTRODUCTION

The availability and deployment of autonomous vehicles, especially fully-autonomous vehicles (AVs), is expected to cause fundamental shifts in the transportation of people and goods. For example, a large number of transportation-related companies have either stated directly or implied that they initially plan to use AVs to provide transportation services to travelers rather than sell individual AVs to consumers for their personal use. While future market adoption depends on many factors, and the extent of individual vs. fleet ownership will be determined by a combination of market forces, economics, and regulatory policy, most future scenarios envision new mobility service businesses models built around some form of shared fleet operation. Given the potential fundamental shift from a society that relies heavily on personal vehicles to one wherein private companies own most vehicles and provide transportation services to individuals with their fleet of vehicles, significant research is necessary to, among other things, maximize the efficiency of the new system. Regardless of market size, AV fleets – even relatively small fleets the size of current car sharing systems – will face new problem classes to manage their fleets to meet customer demand and customer service expectations. Furthermore, planning agencies interested in examining the potential implications of the introduction and adoption of AVs on the transportation network, currently lack the necessary tools to capture the operation of these new forms of mobility. Accordingly, this paper presents a non-exhaustive taxonomy of vehicle fleet management problems in order to [1] introduce the main types of problems likely to be faced by shared autonomous vehicle fleet operators, [2] identify the key differences in cost structure, customer service expectations, and business models between existing problems with human-driven vehicles and problems with AV fleets, [3] help adapt existing algorithms or devise new ones to address these new classes of problems, and thus [4] support future research related to the management of AV fleets.

Over the past 60 years, researchers have developed a vast body of work related to the vehicle fleet management problem. Much of the existing research focuses on routing and scheduling vehicles. Despite a large and diverse literature, the management of AV fleets in urban areas for passenger transportation presents unique modeling challenges such as more stringent constraints on [1] quality of service and [2] the computational time of solution algorithms. Nonetheless, existing fleet management studies provide an excellent foundation for future research related to the AV fleet management problem.

To improve the usefulness of the broad and diverse existing literature we present a taxonomy of fleet management problems. The purpose of a taxonomy is to assist analysts and researchers in identifying the type of problem they are confronting. In addition, once the analyst or researcher is able to identify the characteristics of the problem in question, she can either make use of existing problem formulations and solution algorithms from the literature, if they exist, or begin to define a new problem class and develop original solution algorithms (1, p. 98). In addition to classifying existing fleet management problems, we review existing taxonomic categories in the
literature and present novel taxonomic categories to classify AV fleet management problem classes.

The remainder of the paper is structured as follows. In the next section, we present existing taxonomic categories related to the fleet management problems in the literature, specifically vehicle routing and scheduling problems. Using some of the existing taxonomic categories, we classify the broadly defined AV fleet management problem. Then, we rename and repurpose other existing taxonomic categories in the literature, as well as add additional, and more nuanced, elements to existing categories. In the following section, we present a brief review of dynamic, multi-vehicle pickup and delivery problems with time window constraints, as this class of problems is highly related to the management of AV fleets. The penultimate section presents novel taxonomic categories to classify specific AV fleet management problems. In the final section, we summarize the taxonomy for AV fleets and highlight the need for future research in certain areas.

EXISTING TAXONOMIC CATEGORIES

The field of vehicle fleet management research is incredibly broad and stretches back over six decades (2). Studies range from highly-theoretical to applications of a single problem instance. Hence, it is not surprising that other researchers have presented taxonomies of fleet management problems for various purposes. This section describes some of the taxonomic categories in the existing literature that are relevant to the AV fleet management problem. We begin with the most important categories that draw clear distinctions across problem classes and clearly distinguish the AV fleet management problem. Using some of the categories presented, we classify the broadly defined AV fleet management problem. Additionally, we repurpose and rename other taxonomic categories, as well as, add additional, and more nuanced options within categories.

Pickup and/or Delivery

In their taxonomy of vehicle routing and scheduling problems, Bodin and Golden (1) define a vehicle routing operations category with the following elements:

- Pickups only
- Drop-offs only
- Mixed

The pickups only, and drop-offs only options refer to pure vehicle routing problems (VRPs); whereas, the mixed option is better known as the pickup and delivery problem (PDP), which is a generalization of the VRP. In the PDP, each customer request has unique pickup and delivery locations.

The category name, operations, is too broad for classifying fleet management problems today. Hence, we re-name the category Pickup and/or Delivery.
Classification of the AV Fleet Management Problem

The AV fleet management problem can definitively be classified as a pickup and delivery problem. In urban passenger transportation, travelers have origin and destination points throughout the region where they need to be picked up and delivered, respectively. In fact, the notion of depots, that are synonymous with the VRP, have little meaning in the AV fleet management problem. The reason being that, aside from the problem being a pickup and delivery problem rather than a vehicle routing problem, the problem is also inherently dynamic. The next subsection discusses static and dynamic problems and why dynamic problems are devoid of depots.

Evolution and Quality of Information

Pillac et al. (3) classify VRPs based on two dimensions simultaneously, [1] evolution of information, and [2] quality of information. The evolution of information category classifies problems as static or dynamic; whereas, the quality of information category classifies problems as deterministic or stochastic. The four possible combinations of problems based on this classification pair are described in the following paragraphs.

Static and deterministic: All the routing problem information (i.e. the problem inputs) including customer locations, arc travel times, node service times, etc. are known exactly and significantly before the routing process begins. Once a solution to the problem is found, it is not adjusted during the routing process. In his seminal work, Dantzig (2) formulates a static and deterministic VRP. Laporte (4) reviews problem formulations and solution algorithms for the static and deterministic VRP.

Static and stochastic: In the static and stochastic case, exact information about at least one of the problem elements such as arc travel times, node service times, location of customers, etc. is unavailable. For the problem input(s) in which the modeler does not have exact information, stochastic information is available. All the information, deterministic and stochastic, is known significantly before the routing process begins. Once the routing process begins only minor changes to the vehicle routes are allowed, and these changes do not require communication between individual vehicles (i.e. drivers) and a central operator. Gendreau et al. (5) present a review of static and stochastic VRPs.

Eksioglu et al. (6) present a taxonomy of VRP studies and categorize specific sources of stochasticity including customer service demand quantity, request times of new customers, and on-site service/waiting times.

Dynamic and deterministic: In the dynamic and deterministic case, part, or all the information is unknown to the modeler prior to the beginning of the routing process. The unknown information arrives in real-time, during the execution of routes, to the modeler, typically in the form of customer requests. Vehicles are constantly re-routed in real-time as the unknown information reveals itself. The process of handling new information and re-routing vehicles and reassigning passengers to vehicles in real-time is often referred to as a rolling-horizon solution
approach. Real-time communication and location information are necessary to solve dynamic
problems. Fifteen years ago, this meant separate tracking devices and cell phones or radios;
whereas, now, drivers have smart phones with built-in GPS-capabilities that a central operator
can control without any direct communication with the driver.

**Dynamic and stochastic:** In the dynamic and stochastic case, part, or all the information reveals
itself to the modeler in real-time. However, the modeler can exploit stochastic information about
the unknown information in routing and repositioning vehicles. For example, if the location and
time of future demand requests are unknown, but probabilistic information on the frequency of
demand requests across the region is known, empty vehicles can be re-positioned to areas where
expected future demand is high. Once again, real-time communication and location information
are necessary to solve the dynamic problem because routes need to be re-calculated in real-time.

In the literature, the dynamic problem is also referred to as the real-time problem (7) and the
online problem (8, 9). As mentioned previously, compared with the static problem wherein the
problem only needs to be solved once, the dynamic problem needs to be constantly re-solved in
real-time as new information arrives. One way to solve the dynamic problem is to solve a static
problem with all the currently available information whenever new information reveals itself.
However, the VRP is an NP-hard problem meaning that even moderate size instances of the
problem cannot be solved, exactly, in a reasonable timeframe; hence, heuristics are typically
employed.

Savelsbergh & Sol (10) point out that in the dynamic problem, the notion of vehicle depots is not
applicable because, as new customer requests arrive in real-time, and the static problem needs to be
re-solved, vehicles are located throughout the operational area, not at fixed depots.

**Classification of the AV Fleet Management Problem**

The AV fleet management problem is an inherently dynamic problem as most information
reveals itself in real-time, such as, passenger pickup and delivery times and locations, arc travel
times, passenger service times, etc. The AV fleet management problem can be modeled as
dynamic and deterministic, or dynamic and stochastic depending on the modeler assumptions
and the availability of stochastic information.

In a later section, we further classify problems based on the evolution of information. Lund et al.
(11) define and present a mathematical formulation for the term *degree of dynamism*, which
takes into account the frequency of changes in information knowledge (e.g. new customer
requests) and the urgency of the requests (i.e. how soon after making a request does the
passenger want to be picked up).

**Availability and Processing of Information**

In addition to evolution and quality of information, Eksioglu et al. (6) include two other
subcategories under the information characteristics category in their VRP taxonomy. The two
subcategories include availability of information and processing of information. The availability
of information taxonomic elements are:

- Global
- Local

and the processing of information taxonomic elements are:

- Centralized
- Decentralized

In the present day, most AV fleet managers presumably have global information about the
location of AVs and customer requests within an urban area. However, given the computational
complexity of routing, scheduling, and assigning vehicles, decentralized, as well as centralized
computing architectures are both likely to be seen in practice. Smaller fleets may be able to
employ a single centralized computing system; whereas, larger fleets may require a decentralized
computing architecture.

**Time-Window Constraints**

In their taxonomy of vehicle routing and scheduling problems, Bodin and Golden (1) define a
vehicle routing *time to service a particular node or arc* category with the following elements:

- Time specified and fixed in advance (pure vehicle scheduling problem)
- Time windows (combined vehicle routing and scheduling problem)
- Time unspecified (in this case, we have a vehicle routing problem unless there are precedence
relationships as well, in which case we have a combined vehicle routing and scheduling problem)

We repurpose and rename this taxonomic category and in doing so remove the pure vehicle
scheduling problem option and reduce the ambiguity of the time unspecified option. The updated
category, *time-window constraints*, includes the following elements:

- No time-windows
- Explicit time-windows
- Implicit time-windows
- Explicit and implicit time-windows

In our classification system, the no time-windows problem allows the fleet operator to serve
demand requests at any time; whereas, the problems with explicit and/or implicit time-windows
force the fleet operator to serve demand requests with specified time-windows. The difference
between explicit and implicit time-windows manifests itself in the mathematical formulation of
the problem. Explicit time-window constraints are hard constraints on the problem’s objective
function; whereas, implicit time-window constraints are placed in the objective function.
Lagrangian relaxation can be used to convert explicit time-window constraints into implicit time-
window constraints. Implicit time-window constraints in the objective function are often referred
to as the quality of service term. Eksioglu et al. (6) present a similar classification category
entitled *time window structure* with the following elements, soft-time windows, strict time
windows, mix of both. The pickup and delivery problem with time-windows (PDPTW) is a well-known problem with passenger and freight applications (12–14).

Classification of the AV Fleet Management Problem

The AV fleet management problem is a combined vehicle routing and scheduling (and assignment) problem. The problem can be formulated with explicit and/or implicit time-window constraints depending on the problem instance. For example, transportation network companies (TNCs) such as Uber and Lyft seem to operate with implicit time-window constraints (customers are picked up as soon as possible); whereas other transportation service companies provide their customers with explicit time-windows.

Other Bodin and Golden Taxonomic Categories

Bodin and Golden (1) present a taxonomy of vehicle scheduling and routing problems. We present and discuss the categories in their taxonomy to highlight changes to the taxonomy and to classify the broadly defined AV fleet management problem.

Size of Vehicle Fleet Available

Bodin and Golden (1) list the following taxonomic elements for their size of vehicle fleet available category:

- One vehicle
- More than one vehicle

This category may appear to be superfluous but in terms of developing a modeling framework, formulating the mathematical program, and developing a solution algorithm, the distinction is important. The AV fleet management problem is, by definition, a multiple vehicle problem.

Type of Vehicle Fleet

Bodin and Golden (1) list the following taxonomic elements for their type of vehicle fleet category:

- Homogenous (all vehicles are the same)
- Heterogeneous (not all vehicles are the same)

Eksioglu et al. (6) include four elements in their vehicle homogeneity (capacity) category, including:

- Similar vehicles
- Load-specific vehicles (each vehicle can be used to handle a specific load)
- Heterogeneous vehicles
- Customer-specific vehicles (a customer must be visited by a specific type of vehicle)

Once again, there are large differences in terms of formulating and solving homogenous and heterogeneous fleet management problems. In terms of future research on the AV fleet management problem, the distinction between homogenous and heterogeneous is still important.
Future research needs to consider both the homogenous and heterogeneous cases as both types of AV fleets are likely to be implemented in practice. We prefer the vehicle homogeneity category title in Eksioglu et al. (6).

Location of Demands

Bodin and Golden (1) list the following taxonomic elements for their location of demands category:

- Nodes
- Arcs
- Mixed

The AV fleet management problem is not an arc routing problem; however, if the network representation is a road network, demand points can be located along an arc. If the modeler defines a completely-connected virtual network, without modeling the underlying road network, demand points are best modeled as individual nodes. However, if the network structure incorporates the underlying road network, the pickup and delivery points are likely to be located along arcs in the network.

Underlying Network

Bodin and Golden (1) list the following taxonomic elements in their underlying network category:

- Directed
- Undirected
- Mixed

In the Novel Taxonomic Categories section, we repurpose this taxonomic category and present a more nuanced classification of the underlying networks used to model the AV fleet management problem. We rename Bodin and Golden’s underlying network taxonomic category as arc directionality.

Vehicle Capacity Constraints

Bodin and Golden (1) list the following taxonomic elements for their vehicle capacity constraints category:

- Imposed all the time
- Imposed some of the time
- Not imposed

Once again this is an important modeling consideration. In terms of the AV fleet management problem, all three possibilities should be considered. If the AVs are similar to sedans, and shared rides or ride-matching takes place, then capacity constraints should be imposed all the time. However, if the AV fleet of sedans only provides direct origin to destination service to travelers, then capacity constraints are probably unnecessary. If the AVs are like buses or large vans,
capacity constraints might be considered in some cases and not others depending on overall demand levels.

*Maximum Vehicle Route Times*

Bodin and Golden (1) list the following taxonomic elements for their *maximum vehicle route times* category:

- Imposed – all the same
- Imposed – not all the same
- Not imposed

This classification category has become significantly more interesting and relevant in recent years, especially, if we group maximum vehicle route *distances* with vehicle route *times*. Before listing potentially interesting AV fleet problems related to maximum vehicle route times and distances it is important to remember that Bodin and Golden introduced this classification category in reference to static routing and scheduling problems. In static problem formulations, maximum vehicle route times were included as constraints in the mathematic program. In dynamic fleet management problems, the maximum vehicle route times and distances can take various forms in the modeling framework.

Regarding maximum vehicle route times in the AV fleet management problem, a constraint might be imposed in the case where the AV fleet operator allows ridesharing or shared-rides. If the AV fleet operator allows ridesharing, constraints on the maximum vehicle detour time to pick up and/or deliver additional passengers are possible. Lyft imposes such constraints currently for their Lyft Line service (15).

A second possible instance wherein maximum vehicle routing time constraints might be imposed is in comparing the operations of a conventional vehicle fleet with drivers, to an AV fleet. One of the important questions companies are asking is how much more cost-efficient are AVs than non-AVs in terms of their operational costs. Aside from the fact that there are no labor costs associated with AVs, AVs will likely not be subject to labor rules such as a maximum number of hours on the road per day.

In regards to maximum vehicle route *distance*, this constraint is especially relevant when it comes to modeling electric AV fleets. Most electric vehicles have limited range compared to gasoline-powered vehicles and electric battery charging stations are sparse compared to gasoline refueling stations. In terms of modeling maximum vehicle route distances in a dynamic modeling framework, it is necessary to keep track of the distance each AV has traveled since refueling. This is usually captured through a *state* variable.

In other AV fleet management problems, modeling maximum vehicle route time and distance constraints may not be necessary. Such instances include modeling the morning-peak period with a gasoline-powered AV fleet.
Costs

Bodin and Golden (1) list the following taxonomic elements in their costs category:

- Variable or routing costs
- Fixed operating or vehicle acquisition costs (capital costs)

In typical routing problems, variable operating costs are included in the objective function. Sometimes fixed vehicle acquisition costs are included in the objective function or as a constraint. This classification category is still relevant to the AV fleet management problem because modeling frameworks may incorporate variable costs, fixed costs, or both. Bodin and Golden provide a taxonomy of routing and scheduling problems, whereas this paper provides a taxonomy for vehicle fleet management problems. Hence, while classic routing and scheduling problems cannot seamlessly incorporate pricing, vehicle fleet management problems can handle pricing. In the Novel Taxonomic Categories section, we classify pricing strategies.

Objective

Bodin and Golden (1) list the following taxonomic elements in their objectives category:

- Minimize routing costs incurred
- Minimize sum of fixed and variable costs
- Minimize number of vehicles required

Savelsbergh and Sol (10) also classify potential objective functions for the PDP; the elements include:

- Single vehicle objectives
  - Minimize duration
  - Minimize completion time
  - Minimize travel time
  - Minimize route length
  - Minimize client inconvenience
- Multiple vehicle objectives
  - Minimize number of vehicles
  - Maximize profit

Neither of these lists are exhaustive but Savelsbergh and Sol’s list includes significantly more options. The most interesting of which is profit maximization. In order for the problem framework to incorporate profit maximization, the fleet operator must be able to reject customer requests or price discriminate. In the Novel Taxonomic Categories section of this paper we discuss acceptance and rejection of loads as well as pricing options.

Savelsbergh and Sol state that for the dynamic problem, objectives such as duration, completion time, and travel time have no clear meaning. Hence, these objectives are not useful for the AV fleet management problem. However, objectives such as minimizing cumulative travel time and/or wait time and minimizing cumulative vehicle miles traveled are appropriate in the
dynamic context. We list the following as possible objectives for AV fleet management problem classes:

- Maximize profit
- Minimize cost
- Minimize client inconvenience
- Minimize cumulative vehicle miles traveled
- Minimize traveler wait time
- Minimize traveler in-vehicle travel time
- Minimize number of vehicles
- Mixed (i.e. multi-objective)

**BRIEF REVIEW OF DYNAMIC, MULTI-VEHICLE, PDPTW**

In the previous section, we review existing fleet management problem taxonomies. We classify the broadly defined AV fleet management problem as a dynamic, multiple vehicle, pickup and delivery problem with implicit or explicit time window constraints wherein the modeler has global information. In the next section, we present novel classification categories to further classify AV fleet management problem classes. However, we first present a brief literature review of dynamic, multiple vehicle, pickup and delivery problems with implicit or explicit time-window constraints. These studies are highly related to the AV fleet management problem.

Psaraftis (16), in his seminal work on the static and dynamic dial-a-ride problems (DARP), solves a (single vehicle) passenger, pickup and delivery problem with implicit time-window constraints. The implicit time-window constraint manifests itself via a customer ‘dissatisfaction’ term in the objective function that includes passenger wait time and in-vehicle travel time. The DARP and the modeling framework developed by Psaraftis (16) are still applicable to the AV fleet management problem.

Savelsbergh and Sol (10) present a survey of PDPs that includes the dynamic PDP. The authors present useful insights into solving the dynamic PDP. Savelsbergh and Sol (10) classify the PDP based on transportation requests (static or dynamic), time-constraints (transportation request time-constraints and vehicle time-constraints), and objective functions.

Kim (17) and Kim et al. (18) formulate static and dynamic, multi-vehicle PDPs with implicit and explicit time-window constraints. The authors look at truckload service (i.e. no partial loads) with two different types of customer requests, priority and regular, that result in implicit and explicit time-window constraints. Moreover, the modeling framework incorporates load acceptance and rejection decisions, based on stochastic information about future customer requests; therefore, the authors can formulate a profit maximization problem. In the truckload freight problem, the time-windows are significantly larger than in the urban passenger transportation context; nonetheless, Kim’s modeling framework is still useful.

Mitrovic-Minic (19) present a heuristic approach to the dynamic, multi-vehicle, PDP with time-window constraints. The authors use a rolling-horizon solution approach but employ a double-
horizon heuristic that assigns loads to vehicles, and routes and schedules those vehicles based on short-term and long-term horizons. In AV fleet management problem classes in which passengers can reserve vehicles in-advance, this double-horizon approach may be effective.

Sheridan et al. (20) present a dynamic nearest neighbor heuristic for the dynamic, multi-vehicle PDP with service quality considerations. The dynamic nearest neighbor heuristic allows vehicles that have previously been assigned to a customer to be re-assigned if they have not yet picked up their previously assigned customer. Yang et al. (8) also allow for diversion of vehicles when they are en-route to pick up a customer. Yang et al. (7, 8) compare an optimization-based solution approach with simple heuristic solution approaches that are less computationally demanding.

Fleischmann et al. (21) model a dynamic, multi-vehicle PDP with time-window constraints on a network that considers time-dependent traffic congestion. Xiang et al. (22) examine the dynamic DARP also taking into consideration time-dependent congestion and other stochastic problem components.

Other vehicle fleet management problems in the literature related to the AV fleet management problem include the taxi-dispatching problem (23, 24) and the ambulance relocation problem (25).

Survey papers that cover the dynamic multi-vehicle pickup and delivery problem with time-window constraints include: Agatz et al. (26) who focus on dynamic ride-sharing for passenger transportation; Berbeglia et al. (13) who focus on dynamic pickup and delivery problems; and Psaraftis et al. (27) who review three decades of dynamic vehicle routing problems.

**NOVEL TAXONOMIC CATEGORIES**

This section presents novel taxonomic categories to classify various types of AV fleet management problems.

**Fleet Size Elasticity**

- Elastic
- Fixed fleet size

The sharing-economy and TNCs Uber and Lyft motivated this taxonomic category. TNCs have highly elastic fleets, despite not owning any vehicles, because they can set transportation prices to attract drivers. If demand exceeds supply, TNCs can increase transportation prices to both decrease demand and increase supply. The authors of this paper were unable to find any research modeling short-term fleet size elasticity within the context of routing, assigning, or scheduling vehicles. The benefits of the ability to increase or decrease fleet-size to flex with demand are likely significant. Presumably AV fleet managers will be able to increase fleet-size in the short-term by either paying for access to privately-owned AVs or allowing drivers with non-AVs to provide transportation service. This area is ripe for future research.
Reservation Structure

- Short-term (slot-based) rentals
- Point-to-point service
- Mixed

Short-term AV rentals are similar to carsharing except that instead of a user going to a designated carsharing parking spot to access a vehicle, the AV would arrive at the user’s desired point of origin. With short-term rentals, the traveler has complete control over the vehicle for a specified time-slot. Conversely, point-to-point service describes the service currently provided by TNCs, wherein, a traveler requests pickup and delivery points and the vehicle transports the traveler between those two points. With short-term rentals, travelers can temporarily store items in the vehicle such as during a shopping trip. The mixed reservation option describes an AV fleet wherein the vehicles can either provide point-to-point service or be rented to travelers for time-slots. Pricing the mixed fleet option to take into consideration the opportunity costs of not having a vehicle available for the other reservation option is an interesting problem.

Pricing

- No pricing
- Fixed pricing structure
- Pricing, with no fixed structure

Problems wherein the pricing structure is fixed do not allow the fleet manager to price discriminate across customers. Fixed pricing structures include user mileage- and/or travel time-based structures. In problems with no fixed pricing structure, the fleet manager can charge higher rates based on the time-of-day, the location of the customer’s origin and or destination, or as a function of information about competing AV fleets in the area. In competitive transportation markets the rates charged by carriers are usually modeled as a function of the trip’s marginal cost and the price elasticity of demand facing the firm.

A large portion of freight transportation service is outsourced to commercial carriers and pricing structures vary across commercial trucking firms. A significant amount of research exists on pricing transportation service; however, a relatively small amount is integrated within a fleet management framework. Figliozzi et al. (28) present one of the few modeling frameworks that integrates pricing strategies and fleet management. In their model, the carrier needs to calculate the marginal cost of accepting an additional customer request to determine the price to charge customers.

In modeling the AV fleet management problem, not including pricing in the problem framework can still yield valuable results; however, researchers should focus on incorporating various pricing components to increase the behavioral realism of the problem. Moreover, modeling pricing is necessary to subsequently model competition between competing AV fleets.
Accept/Reject Decision

- Unnecessary
- Fleet manager decision
- Customer decision

The accept or reject decision comes into play when the problem’s objective function includes revenue, in addition to costs. In the case where revenue is not considered in the problem framework the acceptance/rejection decision is unnecessary.

If revenue and costs are both considered in the fleet management problem framework, but pricing is fixed, then the fleet manager must accept or reject customer requests as they arrive in real-time. If the marginal operational cost of servicing the customer request exceeds the marginal revenue associated with the request, the fleet manager will likely reject the request. If stochastic information is available, the marginal cost should incorporate the opportunity cost of sending the vehicle to service the customer request.

In the case where revenue is considered in the objective function and the pricing structure is not fixed, the accept/reject decision lies in the hands of the customer. The fleet manager offers the user a price that the user can accept or reject. Currently, TNCs, operate under this model wherein the fleet manager offers a price to the customer through a smartphone application.

Reservation Timeframe (Degree of Dynamism)

- Immediate requests
- Minimum pre-reservation time
- Mixed

Lund et al. (11) introduce the term degree of dynamism and Larsen (29) develops the effective degree of dynamism. The effective degree of dynamism represents, on average, the difference between the time a customer requests service, and the latest possible time the customer request must be served. ‘Immediate requests’ (16) represent requests wherein customers want transportation service as soon as they request a ride. Minimum pre-reservation time represents cases wherein customers must reserve transportation service a pre-defined period of time prior to the time they want to be serviced. In the mixed case, customers can request service immediately or pre-reserve service for a future time-period.

From a fleet operations perspective and a firm profit-maximization perspective, allowing advanced demand requests can be both beneficial and disadvantageous depending on the circumstances. If demand is high relative to fleet size, and the fleet manager can charge high prices to customers making immediate requests, it is disadvantageous to have advanced demand requests for two reasons. First, presumably the advanced demand requests receive ‘locked-in’ rates that are lower than the rates currently being charged by the fleet to immediate demand requests; therefore, the company loses money by serving the advanced demand requests rather than the immediate demand requests. Second, the advanced demand requests add binding
constraints to the vehicle routing and scheduling problem when demand is high. Without the advanced demand requests the vehicles would be free to focus on areas of high demand. Conversely, if demand is low relative to fleet size, it is beneficial to have advanced information on the location and time of demand requests to efficiently route vehicles and minimize empty vehicle miles.

As of early 2016, Uber and Lyft only allowed immediate requests. However, in late 2016, Uber’s mobile phone application in many cities allows passengers to pre-reserve rides.

**Ridesharing**

- No sharing
- Ridesharing

Ridesharing refers to the case wherein a vehicle can transport two different demand requests at the same time. Given a fixed-fleet size, the inclusion of ridesharing typically reduces passenger wait time, but increases passenger in-vehicle travel time. The well-known dynamic DARP includes ridesharing; however, most DARP problems were originally formulated within the context of transporting elderly and disabled travelers who, unfortunately, cannot operate vehicles. In contrast, AV fleet companies are undoubtedly planning to offer service to all travelers, not just those unable to afford and/or operate a vehicle. To attract travelers that are wealthy and healthy enough to own and operate a vehicle, the level of service of an AV fleet will need to be commensurate with owning one’s own vehicle – autonomous or non-autonomous. Hence, the increased importance of level-of-service in the AV fleet management problem, relative to the traditional DARP, will need to be considered in the modeling framework. Level-of-service can be included in the modeling framework via including passenger wait time and passenger travel time in the objective function. Additionally, hard constraints for wait time, travel time, and time-windows can be included in the mathematical formulation of the problem.

**Repositioning**

- No repositioning of vehicles
- Repositioning based on stochastic information

**Underlying Network**

- Real road network
- Test road network
- Graph or Virtual Network (Nodes are pickup and delivery points)

In Bodin and Golden’s taxonomy, their *underlying network* category refers to the directionality of the arcs. We rename their category as *arc directionality* and repurpose the *underlying network* category. In the classic VRP, a network is a combination of depot nodes, customer origin and/or destination nodes, and arcs connecting all or some of these nodes. However, we refer to this type of network as a graph or virtual network because it does not represent a physical road network. Conversely, fleet management problem frameworks can incorporate physical road networks. We
distinguish between real road networks and test road networks. Test road networks include grid
networks designed by the modeler. In road networks, intersections are modeled as nodes and
street segments between intersections are modeled as links.

**Network Congestion**

- No congestion
- Static
- Time-dependent

In modeling frameworks with virtual or real networks, the network links can include congestion.
We mentioned previously that the congestion on links can be deterministic or stochastic.
Additionally, the congestion can be static or time-dependent. In a dynamic AV fleet management
modeling framework, congestion on links can fluctuate based on the time of the day (time-
dependent) or remain constant throughout the analysis period (static).
### TABLE 1 Taxonomy of AV Fleet Management Problems

<table>
<thead>
<tr>
<th>Existing Taxonomic Categories</th>
<th>Remaining Taxonomic Categories to Classify Specific AV Fleet Management Problems</th>
<th>Novel Taxonomic Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Classifying the General AV Fleet Management Problem</strong></td>
<td><strong>Quality of Information</strong></td>
<td><strong>Fleet Size Elasticity</strong></td>
</tr>
<tr>
<td>Pickup and/or Delivery</td>
<td>• Deterministic</td>
<td>• Elastic</td>
</tr>
<tr>
<td>• Pickups only</td>
<td>• Stochastic</td>
<td>• Fixed Fleet Size</td>
</tr>
<tr>
<td>• Deliveries only</td>
<td><strong>Processing of Information</strong></td>
<td><strong>Reservation Structure</strong></td>
</tr>
<tr>
<td>• Pickups and deliveries</td>
<td>• Centralized</td>
<td>• Short-term rentals</td>
</tr>
<tr>
<td><strong>Evolution of Information</strong></td>
<td>• Decentralized</td>
<td>• Point-to-point service</td>
</tr>
<tr>
<td>• Static</td>
<td><strong>Vehicle Homogeneity</strong></td>
<td>• Mixed</td>
</tr>
<tr>
<td>• Dynamic</td>
<td>• Homogenous</td>
<td><strong>Pricing</strong></td>
</tr>
<tr>
<td><strong>Availability of Information</strong></td>
<td>• Heterogeneous</td>
<td>• No pricing</td>
</tr>
<tr>
<td>• Global</td>
<td><strong>Location of Demands</strong></td>
<td>• Fixed pricing structure</td>
</tr>
<tr>
<td>• Local</td>
<td>• Nodes</td>
<td>• Pricing, with no fixed structure</td>
</tr>
<tr>
<td><strong>Time-Window Constraints</strong></td>
<td>• Arcs</td>
<td><strong>Accept/Reject Decision</strong></td>
</tr>
<tr>
<td>• No time-windows</td>
<td>• Mixed</td>
<td>• No decision</td>
</tr>
<tr>
<td>• Explicit time-windows</td>
<td><strong>Arc Directionality</strong></td>
<td>• Fleet manager decision</td>
</tr>
<tr>
<td>• Implicit time-windows</td>
<td>• Directed</td>
<td><strong>Reservation Timeframe</strong></td>
</tr>
<tr>
<td>• Explicit and implicit</td>
<td>• Undirected</td>
<td>• Minimum pre-reservation time</td>
</tr>
<tr>
<td><strong>Size of Vehicle Fleet</strong></td>
<td>• Mixed</td>
<td>• Mixed</td>
</tr>
<tr>
<td>• One vehicle</td>
<td><strong>Vehicle Capacity Constraints</strong></td>
<td><strong>Repositioning</strong></td>
</tr>
<tr>
<td>• Multiple vehicles</td>
<td>• Imposed all the time</td>
<td>• No repositioning</td>
</tr>
<tr>
<td></td>
<td>• Imposed some of the time</td>
<td>• Repositioning based on stochastic information</td>
</tr>
<tr>
<td></td>
<td>• Not imposed</td>
<td><strong>Underlying Network</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Maximum vehicle route times (and distances)</strong></td>
<td>• Real road network</td>
</tr>
<tr>
<td></td>
<td>• Imposed – all the same</td>
<td>• Test road network</td>
</tr>
<tr>
<td></td>
<td>• Imposed – not all the same</td>
<td>• Graph/Virtual Network</td>
</tr>
<tr>
<td></td>
<td>• Not imposed</td>
<td><strong>Network Congestion</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Costs</strong></td>
<td>• No congestion</td>
</tr>
<tr>
<td></td>
<td>• Variable or routing costs</td>
<td>• Static</td>
</tr>
<tr>
<td></td>
<td>• Fixed operating or vehicle acquisition costs (capital costs)</td>
<td>• Time-dependent</td>
</tr>
<tr>
<td></td>
<td><strong>Objective</strong></td>
<td><strong>Fleet Size Elasticity</strong></td>
</tr>
<tr>
<td></td>
<td>• Maximize profit</td>
<td>• Elastic</td>
</tr>
<tr>
<td></td>
<td>• Minimize cost</td>
<td>• Fixed Fleet Size</td>
</tr>
<tr>
<td></td>
<td>• Minimize client inconvenience</td>
<td><strong>Reservation Structure</strong></td>
</tr>
<tr>
<td></td>
<td>• Minimize vehicle miles traveled</td>
<td>• Short-term rentals</td>
</tr>
<tr>
<td></td>
<td>• Minimize traveler wait time</td>
<td>• Point-to-point service</td>
</tr>
<tr>
<td></td>
<td>• Minimize traveler in-vehicle travel time</td>
<td>• Mixed</td>
</tr>
<tr>
<td></td>
<td>• Minimize number of vehicles</td>
<td><strong>Pricing</strong></td>
</tr>
<tr>
<td></td>
<td>• Mixed (i.e. multi-objective)</td>
<td>• No pricing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Fixed pricing structure</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Pricing, with no fixed structure</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Accept/Reject Decision</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• No decision</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Fleet manager decision</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Reservation Timeframe</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Immediate requests</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Minimum pre-reservation time</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Mixed</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Repositioning</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• No repositioning</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Repositioning based on stochastic information</td>
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<td></td>
<td></td>
<td>• Time-dependent</td>
</tr>
</tbody>
</table>
SUMMARY

This paper presents a taxonomy of fleet management problem classes to inform future research on the AV fleet management problem. We begin by reviewing previous taxonomies of the vehicle fleet management problem, specifically, vehicle scheduling and routing problems. We refine several taxonomic categories from these studies to provide more nuance and better classify problem classes as they relate to the AV fleet problem. In the following section, we present a brief literature review of dynamic multi-vehicle, pickup and delivery problems with time-windows. While the AV fleet management problem presents unique modeling challenges, many of the papers surveyed provide a valuable foundation for future work. Lastly, we present several novel taxonomic categories to classify AV fleet management problems.

Table 1 displays a summary of the taxonomy developed in this paper. The first column displays taxonomic categories in the literature that we use to classify the broadly defined AV fleet management problem. The underlined terms in the first column of Table 1 signify that the AV fleet management problem is a dynamic, multi-vehicle pickup and delivery problem with explicit or implicit time-window constraints wherein the AV fleet manager has global information. The second column in Table 1 lists taxonomic categories in the literature that are still relevant in terms of classifying AV fleet management problem classes. The third column lists novel taxonomic categories presented in this paper to classify AV fleet management problems.

The taxonomy presented in this paper, specifically the categories in the second and third columns of Table 1, illustrate the wide-range of problem classes that still need to be investigated to model and analyze AV fleets. The two most significant areas where foundational research is lacking are the advantages of short-term fleet elasticity and the role of pricing strategies on the management of an AV fleet. The ability to increase and decrease fleet size in a short period of time seems to be one of the more underappreciated elements of TNC business models. Additionally, in a dynamic, competitive context, pricing is one of the most important elements in modeling vehicle fleet operations. The pricing problem significantly impacts the assignment of vehicles to customers and the routing of vehicles. The literature examining transportation pricing and fleet management in an integrated framework is sparse (28). Other interesting problems relate to vehicle repositioning strategies based on time-dependent stochastic information, the modeling of refueling strategies for electric vehicles, and the inclusion of short-term rentals in the modeling framework.
REFERENCES


pp. 130–154.


