HART Autonomous Vehicle Study: Generating Household Travel-Activity Patterns with Autonomous Vehicles

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May 24, 2023

Prepared by the Honolulu Authority for Rapid Transportation in Cooperation with the Oahu Metropolitan Planning Organization and the United States Department of Transportation

This report was funded in part through grants from the Federal Highway Administration and Federal Transit Administration, U.S. Department of Transportation. The views and opinions of the agency expressed herein do not necessarily state or reflect those of the U.S. Department of Transportation.

Summary

Introduction and Background: This study investigates the impacts of autonomous vehicles (AVs) on household travel-activity patterns in the Oahu MPO study area. Over the past decade, Honolulu households have faced several emerging mobility options. These range from the start of Biki bikeshare in 2011, Lime e-scooters in 2018 and the opening of the Honolulu Authority on Rapid Transportation (HART) Rail System, scheduled for the summer of 2023. Future scenarios for the region include autonomous vehicles, which are anticipated to weave into the set of household mobility options. *Forecasting for regional scenarios characterized by these mobility options begins with understanding the potential changes they bring to household travel patterns, including the scheduling of out-of-home activities.* The overarching goal of this study is to understand how AVs and the HART rail system would potentially shift household travel patterns, leading to varying benefits and feasibility. Through this study, we address the following broad questions:

A) *Which households will benefit from AVs, with respect to their travel patterns?* With respect to regional travel patterns, while the regional benefits from AVs have broadly envisioned and discussed, the impacts to households or other decision makers are less clear. This study begins to address the question of *who* potentially benefits, while recognizing that these impacts are contingent on future conditions which face varying uncertainties.

B) *How will the HART rail system affect AV impacts on households?* Parallel to the expectation of AVs is the opening of the HART rail system. This study also considers how to account for the impacts from the availability of the rail.

Analysis Approach: Forecasting travel-activity patterns requires a *crystal ball* or forecasting tools, conventionally accomplished with a model, which could be a computer simulation, econometric and/or machine learning-based, synthesis of real-world case studies, or a combination of the above. Developing forecasting tools begins with models that reflect travel-activity pattern changes. In this study, we adopt the perspective of households as service providers that dispatch a vehicle fleet to service out-of-home activities. Analogous service systems include delivery logistics providers (e.g. FedEx, UPS, USPS, DHL, etc.), rideshare TNCs (e.g. Uber, Lyft, etc.) and emergency service providers (EMS, Municipal Fire Departments, etc.).

From this perspective, households have a set of out-of-home activities that need to be completed; they must decide how many household vehicles to dispatch, their routing and their scheduling of stops (timing and sequencing). The transportation systems literature refers to this class of decision problems as the *Vehicle Routing Problem (VRP)*, which includes its variations. These include a VRP with (a) pick-up/deliveries; (b) time windows and schedule constraints; (c) multimodal fleets and (f) others operational constraints of the decision-making context. Conventionally, these problems are driven by the objective of optimizing along relevant dimensions, such as travel time, travel cost and other performance metrics.

In this study, for the households in the 2012 Oahu Household Travel Survey, we solve a VRP with pick-up/deliveries for their required set of out-of-home activities; these are observed in their daily

patterns collected from the survey. We consider a decision context where the objective is to minimize travel and idle times of an AV fleet. AVs are assumed to be *Level 4*, with full autonomy and other operational characteristics derived from the literature. For example, these include envisioned futures where AVs pick-up groceries or other complete other services without human intervention, or where an AV operates as a taxi service, dropping-off/picking-up human passengers with no parking requirements (Cusack 2021). Schedule activity constraints are assumed, based on activity type. For example, we assume grocery shopping activity start times have a time window of 9AM-10PM. School and work activities are assumed to have a very strict narrow time window reflective of their mandatory nature. While these assumed constraints will likely differ from real-world constraints faced by each individual traveler, to operationalize the modeling approach and arrive at a solution, assumptions were necessary.

Solving the Household VRP: The literature as established that solving the VRP class of problems is NP-hard, indicating that the computational time to reach a solution increases infeasibly (non-polynomial time) as the size of the problem (number of stops, network size, etc.) increases. Given our defined Household VRP, a set of heuristics were used to feasibly solve the VRP for our analysis sample of 2,967 households. Heuristics used in this study include: (a) Clark-Wright Savings (CW) and (b) the Node Insertion family (N1, N2, N3) of heuristics (Solomon 1987). Each heuristic and their assumed set of parameter values result in solutions that favor different metrics, such as vehicle travel time or idle time. A comparison performance for these heuristics was completed.

Results and Conclusions: *Which households will benefit?* – To assess potential benefits and reasonable responsiveness of households with AVs, we evaluated changes in performance metrics between the status quo and different AV scenarios. The status quo travel-activity pattern, for each household, is assumed to be their observed travel-activity patterns from the 2012 Oahu Household Travel Survey. Their AV scenario patterns were the final solutions solving their respective Household VRP with each heuristic. Performance metrics considered include the total travel time across all household vehicles and the total number of vehicles required to complete the set of out-of-home activities. Network performance metrics (travel times on link, routes, etc.) were taken from the Oahu Travel Demand Forecasting Model (TDFM).

To provide a basis for discussion or results, the planning districts defined by the Oahu MPO were used to characterize households spatially across Oahu. Given the assumptions of this study, with respect to AVs, households in the Wai'anae and East Honolulu districts stand to benefit in terms of total household travel time savings, relative to the existing pattern, controlling for other household characteristics. Relative to other planning districts, the average marginal improvement from households in these two planning districts have the following ranges, depending on district: Wai'anae – 13.7 to 15.2 minutes; East Honolulu – 6.7 to 9.6 minutes. These two planning districts show consistent marginal benefits from having an AV fleet. Model results also indicate that the Ewa planning district had an estimated marginal total travel time improvement of 11.9 minutes per household under an AV context, while the Ko'olau Loa district showed a marginal increase of 21.4 minutes, but for only for one set of heuristic parameters. With respect to the number of household vehicles required, under the AV scenario, all heuristic solutions produced a reduction, except for travel-activity patterns produced from the Clark-Wright Savings (CW) heuristic.

How will the HART system affect the impacts of AVs on Households? – For scenarios where the HART system was introduced, the change in impacts from AVs was marginal. However, this was under the conservative assumption that only households observed using an express bus route on The Bus system would try to incorporate HART for at least a portion of their travel chain segment in combination with an AV. To fully understand the impact of the HART station, future ridership levels, including household demographics, would need to be determined.

1.0 Introduction and Background: Mobility in Honolulu

In the Oahu MPO study area, 70 percent of households are within one-quarter mile of a bus stop, and approximately two-thirds of residents drive alone to work. Additionally, the average commute time by public transportation takes approximately twice as long as the average commute time by car. Many residents state that public transportation services average between 30 minutes to an hour, and they need to make multiple transfers to reach a destination only a few miles from their household origins (OMPO 2021; Lyte 2018). Those who live in the rural and urban fringe areas of Oahu expressed that public transportation services, such as *TheBus* and *TheHandi-Van*, are limited compared to urban Honolulu. These issues are documented in the Mobility Report for the Oahu MPO area (OMPO, 2021). Within this mobility context, Honolulu households have witnessed several emerging mobility options for travelers. These range from *Biki* bikeshare in 2011, Lime e-scooters in 2018 and the opening of the *Honolulu Authority on Rapid Transportation Rail System (HART)*, set for 2023. In the future, autonomous vehicles are also anticipated to weave into the set of mobility options. Forecasting for regional scenarios characterized by these mobility options begins with understanding the potential shifts they bring to household travel-activity patterns, including the scheduling of out-of-home activities.

The overarching goal of this study is to understand how the introduction of AVs and the HART system to Oahu could potentially change household travel patterns. Through this study, we address the following broad questions:

A) Which households will benefit from AVs, with respect to their travel patterns? With respect to regional travel patterns, while the regional benefits from AVs have broadly envisioned and discussed, the impacts to households or other decision makers are less clear. This study begins to address the question of *who* potentially benefits, while recognizing that these impacts are contingent on future conditions which face varying uncertainties.

B) How will the HART rail system affect AV impacts on households? Parallel to the expectation of AVs is the opening of the HART rail system. This study also considers how to account for the impacts from the availability of the rail.

The remainder of this section presents background literature on the definitions and concepts related to autonomous vehicles and modeling their impacts on travel-activity behaviors. This is followed by sections on the presentation of the analysis framework and results.

1.1 Autonomous Vehicles (AVs): Definitions and Concepts

Significant improvements in vehicle communication and sensor technologies have resulted in an increasing interest in estimating the potential benefits of autonomous vehicles (AVs) among transportation planners and policymakers (Anderson et al. 2014). The National Highway Traffic Safety Administration (NHSTA) proposed characterizing AVs on a scale from level 0 to 4, where level 0 refers to complete driver control and level 4 refers to vehicles that perform all safety-critical functions for the entire trip with no expected control from drivers (USDOT 2015). Less attention has been paid to how travelers will eventually use AV for completing activity programs, especially given a household fleet of other mobility resources. In comparison to other emerging vehicle technologies in the past, such as electric vehicles (EVs), AVs present a wider latitude of operational characteristics that differ from conventional vehicles.

1.2 Autonomous Vehicles (AVs): Modeling Travel/Activity Patterns

Investigating the behavioral implications of AV on household travel and activity patterns opens the door to a wide range of methodological directions under the umbrella of activity-based approaches to travel analysis. Under this approach, travel is a derived demand from the need to participate in activities, subject to space-time constraints. Recognizing that individual trips are components integrated into a more complex travel and activity pattern, an impressive body of research work has been produced that model and operationalize this perspective (Rindt and McNally, 2007; Timmermans and Zhang, 2009; Pinjari and Bhat, 2011). Within this literature, four main directions have emerged for modeling travel and activity patterns.

Constraint-Based: One direction witnessing considerably contribution from geographers, planners and engineers focuses on the space-time constraints of activities (Hägerstraand 1970). Using an activity program as input, these models consider the feasibility of a set of patterns with respect to a set of constraints, such as business hours for commercial or retail organizations. An activity program characterizes a set of activities and their associated durations and time windows. The number of feasible activity schedules, subject to these constraints, is often used as a measure of flexibility in space-time environments faced by travelers (Ettema and Timmermans, 2007, Lee et al. 2009). These space-time constraints are usually characterized by (a) potential activity locations; (b) travel mode and accessibility; and (c) network travel times and costs between locations per travel mode. Additionally, these constraints reflect (i) the sufficiency of time duration between the end time of the previous activity and start time of the next activity; (ii) the earliest possible start time and latest end time; and (iii) activity sequencing conditions.

Implemented constraint-based models have been produced since the inception of the activity-based approach, which include PESAP (Lenntorp 1979) and CARLA (Jones et al. 1983), and more recent ones including MASTIC (Dijst and Vidakovic 1995) and GISICAS (Kwan 1997). An advantage of constraint-based models is the ability to determine a feasible set of potential activity patterns versus a single preferred path from a pre-defined set of alternatives. However, with respect to forecasting and prediction, these models currently cannot easily account for adjustment and/or rescheduling which are likely caused by changes in space-time constraints (Lee and McNally 2003, Roorda and Miller 2005, Joh et al. 2008).

Econometric: A second approach views activity patterns as the outcome of utility-maximizing decisions or choices, which serve as a theoretical foundation of econometric models of discrete choice. Given a choice set of activity patterns, each alternative is assumed to be adequately represented as bundles of attribute levels, each contributing to the overall utility of the alternative. The body of research work on discrete choice modeling and travel and activity patterns is vast and intellectually rich, examining a broad range of dimensions, from in-home vs. out-of-home (Akar et al. 2011), to choices among complete activity-travel patterns (Bowman and Ben-Akiva 2001) and rescheduling adjustments (Sun et al. 2005). These econometric approaches capture preferences for one single pattern over another with respect to combinations of attributes levels.

Simulation and Process – A third approach conceptualizes activity scheduling as a process that can be modeled and simulated through computational methods, such as agent-based modeling and other simulation approaches. As a basis for the decision models and their associated behavioral parameters, several of these models incorporate econometric discrete choice models of scheduling decisions (Recker et al. 1986; Kitamura Fujii 1998, Arentze and Timmermans 2009). Validating the decision rules used is a major hurdle for these models. These approaches explicitly recognize and embrace the complexity in modeling travelers' scheduling process, in contrast to oversimplifying through a trip-based model system. These decision process models represent one distinct promising direction for operational models, but, perhaps more importantly, they easily provide a testbed for alternative activity scheduling behavior conceptual frameworks.

Mathematical Programming or Vehicle Routing Problem (VRP) Approaches: A fourth approach considers household activity patterns as an outcome or solution to optimizing an objective function in the form of a generalized cost function with a set of space-time constraints. From this perspective, these models share the ability to consider feasible space-time activity patterns like constraint-based approaches and have the potential for capturing utility-maximizing decision rules like discrete choice models. Within the transportation analysis literature, one example is the Household Activity Pattern Problem (HAPP) formulation developed by Recker (1995) in response to limitations in the STARCHILD model (Recker et al. 1986). The HAPP model is a variation of the "pick-up and delivery problem with time windows" (PDPTW) common in operations research. Households will "pick-up" activities at various locations, accessing these locations using household transportation resources and reflecting interpersonal and temporal constraints, and "deliver" these activities by completing a tour and returning home. HAPP is constructed as a mixed-integer mathematical program and explicitly reflects a full range of travel and activity constraints. Since its introduction, the HAPP model has been extended to account for rescheduling, stochastic activity completion (Gan and Recker, 2013) and locations (Kang and Recker 2013). A recent application also integrates HAPP with the network design problem (Kang et al. 2013). Additionally, HAPP has been applied to a wide range of contexts, such as traffic control for vehicle emissions (Recker and Parimi 1999) and refueling hydrogen fuel vehicles (Kang and Recker 2014). An important methodological issue is the estimation of parameters in the objective function in HAPP, which would interest many in the travel analysis community concerned with operationalizing HAPP with travel-activity data from conventional datasets. Two main approaches have surfaced in response to this need. The first uses similarity metrics to infer the relative importance of spatial and temporal factors associated with out-of-home activities. A more recent effort to calibrate HAPP with larger datasets approaches the problem as an inverse optimization problem, where the decision variables are the coefficients of the cost function, given an optimal path (Chow and Recker 2012). HAPP holds great potential for extensions, both as a pure activity-based framework and as a bridge to conventional discrete choice models of travel behavior.

1.3 Synthesis

Autonomous vehicles are considered in the range of emerging mobility options for metropolitan regions, such as Oahu. While their real-world adoption at the consumer level is beyond the near future, forecasting for long-range transportation planning scenarios will require considering their impacts on households travel patterns. Several methods exist in the literature for modeling these impacts. The next section describes the modeling approach taken in this study based on the literature.

2.0 Analysis and Modeling Framework

Forecasting regional travel-activity patterns requires a *crystal ball*, conventionally accomplished with methods such as computer simulations, data-driven econometric or machine learning approaches, synthesizing case studies, or a combination of the above. Developing forecasting tools sensitive and responsive to future contexts with new mobility options, begins with developing models that reflect travel pattern changes in response to difference contexts, such as adoption of AVs. This requires understanding these changes and their directions. The analysis and modeling framework for this study is summarized in Figure 1 below. The framework begins with the perspective of households as vehicle fleet dispatchers with out-of-home activities that need to be completed. Data on the scheduling constraints and transportation system performance levels (travel times, etc.) are assembled for each household's individual VRP.

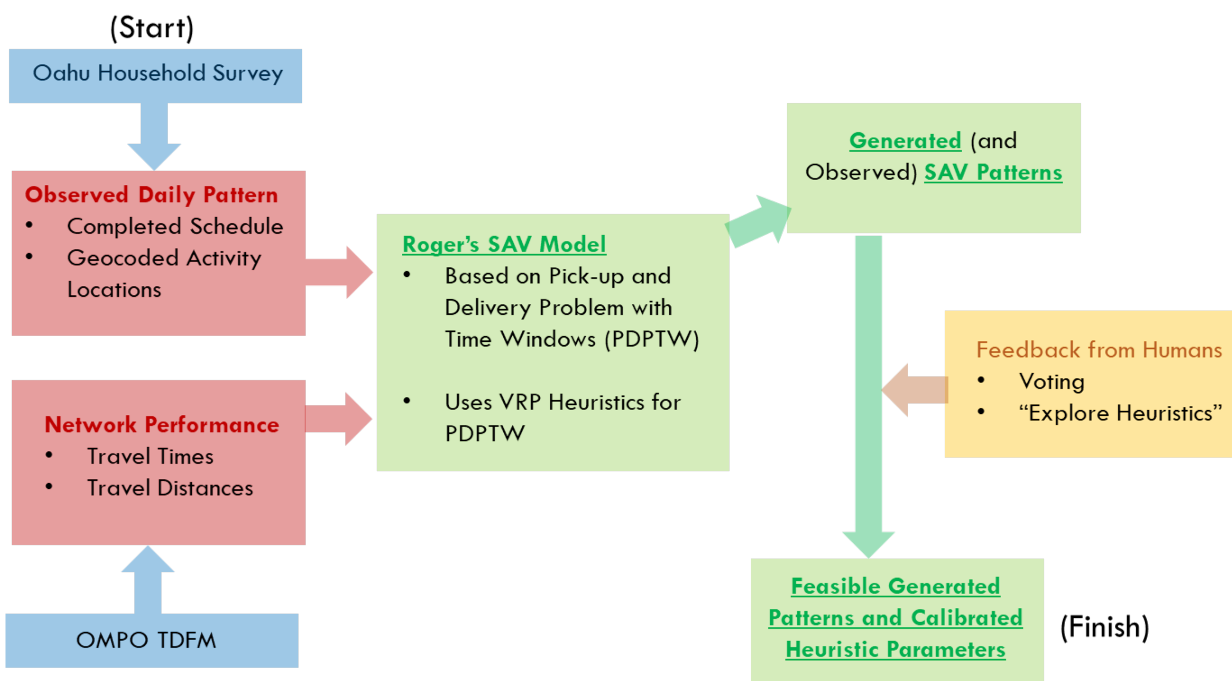

Figure 1. Study Modeling Approach and Framework

In this framework, we view households as analogous to service systems such as delivery logistics providers (e.g. FedEx, UPS, USPS, etc.), rideshare TNCs (e.g. Uber, Lyft, etc.) and emergency response services (EMS, Municipal Fire Departments, etc.). *From this perspective, households have a set of out-of-home activities that need to be completed; they must decide how many household vehicles to dispatch, their routing and their scheduling of stops (timing and sequencing).* This decision problem is known in the literature as the *Vehicle Routing Problem (VRP)* and its variations. These include VRPs with (a) pick-up and deliveries; (b) time windows and schedule constraints; (c) others operational constraints of the decision context. Conventionally, these decisions are driven by the objective of optimizing along dimensions, such as travel time, travel cost and other performance metrics.

After the assembly of network performance and schedule constraint data from the 2012 Oahu Household Travel Survey and the OMPO Travel Demand Forecasting Model (TDFM), respectively, we solve each household's individual VRP. Specifically, we solve the VRP for the set of out-of-home activities in their daily observed pattern. We consider a decision context with "pick-up/delivery of activities" and the objective of minimizing travel time and idle time of the vehicle. AVs are assumed to be *Level 4*, with full autonomy and other operational characteristics derived from the literature. For example, these include AVs picking up groceries or completing other services without human intervention. This also includes the envisioned function as a taxi service dropping-off/picking-up human passengers with no parking (Cusack 2021).

2.1 Activity Scheduling Constraints

To operationalize the household VRP (described in the following section), schedule constraints faced by household activities requiring completion need to be defined. The literature provides little guidance on how to determine these schedule constraints. While there is a sizeable amount of literature on travel time and cost budgets faced by individual and households, operationalizing a household VRP also requires acceptable time windows for activity start times. For example, we may observe a household with a grocery shopping activity beginning at 4:35PM in the Oahu Household Survey. However, from a scheduling perspective, the time window may be as wide as the store hours or as narrow as a 30-minute time window, due to other constraints faced by the households. Without further study, knowing the scheduling constraints faced by specific households is difficult to determine. Regardless, we assume schedule constraints based on the type of activity to operationalize the household VRP. An example of the reasoning that underlies our assumptions are school and work activities, which are assumed to have a very narrow time window reflective of their mandatory nature. Once again, while these assumed schedule constraints will likely differ from real-world constraints faced by each individual traveler, to operationalize the modeling approach, they were necessary. The assumed schedule constraints on start times are presented below in Table 2.

Activity Type	Rule
Mandatory with "hard" Start Times	Within 30 mins +/- of observed start time
Maintenance Shopping	Published Store Hours
Government Office Visits or Services	Published Service Hours
Social and Recreational	Within 60 mins +/- of observed start time
All Other Activities	5AM-10PM (feasible day)

Table 1: Assumed Activity Start Time Constraints

Additionally, activity finish time constraints were also assumed, but with less restrictiveness than activity start times. Activity durations were taken from Oahu Survey Sample. For example, if households observed eating for 1.5 hours, then the eating activity was assumed to require 1.5 hours in duration in subsequent analysis. Given the set of out-of-home activities with their schedule constraints (activity start/finish time windows and durations), for our household sample, a VRP is solved for each household.

2.2 Household Vehicle Routing Problem (VRP)

The mathematical programming approach is adopted for its ability to account for sequencing and timing of activities and/or location visits relative to an objective function of generalized costs and space-time constraints. Additionally, this approach easily allows for the exploration of alternative scenarios characterized by varying constraints and objective function specifications. While several extensions have been made since the first introduction, to provide a foundation from which to make extensions to in-vehicle activities the original HAPP formulation (Recker 1995) was used as the starting point. To take advantage of previous work, a deliberate attempt was made to maintain, to every extent possible, both the notation and structure of the original HAPP model. While many AV operations could be considered, such as dropping off one passenger at one location then picking-up a second passenger at a second location, this study only examines extensions dealing with in-vehicle activities, which are impossible or very difficult for drivers of conventional vehicles for safety reasons.

Consider the activity program where a set of mandatory activities n and a set of IV activities can be completed in-vehicle in an autonomous vehicle or similar mobility service. An activity program characterizes a set of activities and their associated durations and time windows. The following notation is adopted:

$A = \{1,2,\dots,n,n+1,\dots,n+IV\}$	Set of $n + IV$ out-of-home activities scheduled for completion by household travelers; a total of n mandatory activities can only occur out-of-vehicle; a total of IV activities can only occur in-vehicle (this is relaxed in a later extension);

$V = \{1,2, \dots, \|V\|\}$	Set of autonomous or conventional vehicles used by travelers in the household to complete their scheduled activities;
$P^{+} = \{1, . . , n\}$	Set designating the locations for mandatory activities that can only be completed at these locations;
$P_{IV}^{+} = \{n+1, \dots, n+IV\}$	Set of in-vehicle activities that can *only* be completed in-vehicle;
$\bar{P}^{+} = P^{+} \cup P_{IV}^{+}$	Set of all activity pickups;
$P^{-} = \{n+IV+1, n+IV+2, \dots, 2n+IV\}$	Set designating the ultimate destinations of return-to-home trips for each pickup in P^{+};
$P_{IV}^{-} = \{2n+IV+1, \dots, 2n+2IV\}$	Set designating the ultimate locations for in-vehicle activities in P_{IV}^{+};
$\bar{P}^{-} = P^{-} \cup P_{IV}^{-}$	Set of all activity drop-offs;
$P = \bar{P}^{+} \cup \bar{P}^{-}$	Set of all pick-up and drop-off nodes;
$N = \{0, P, 2(n+IV)+1\}$	Set of all nodes, including those associated with the initial and final departure from home;
$[a_i, b_i]$	The time window for the available start times for activity *i*;
s_i	The duration of activity *i*;
t_{uw}	The travel time from the location of activity *u* to activity *w*;
c_{uw}^{v}	The travel cost from location of activity *u* to *w* for vehicle *v*;

B_c	The household travel cost budget;
B_t^v	The household travel time budget for vehicle *v*;

This formulation implies that different elements of $\bar{P}^+$ can potentially correspond to the same physical location. All elements of $\bar{P}^-$ correspond to the same physical location (home). Consequently, the travel time and costs between all drop-off nodes are assumed to be zero: $t_{u,w}^v = c_{u,w} \equiv 0 \;\; \forall \;\; u, w \in \bar{P}^-, \;\; v \in V$.

Consistent with the HAPP formulation (*1*), activities are viewed as being 'picked up' for mathematical purposes by a particular household member at the location where they are performed. Once completed with a service duration s_i, these activities are 'dropped-off' or 'delivered' on the return trip home. Multiple pick-ups are analogous to multiple sojourns or sub-tours for any given tour.

Given a household's objective function, the routing and scheduling policy generated represents a space-time diagram germane to the travel behavior analysis literature. Additionally, demand functions and vehicle capacity (D) ensure that the schedule of pickups and deliveries do not violate any vehicle capacity constraints. For this study, define the capacity D as the maximum number of activities serviced within a tour, with demand function: $d_u = 1, u \in \bar{P}^+$.

The decision variables in this formulation are directly analogous to those of the HAPP and PDPTW formulations and are defined as follows:

$X_{uw}^u, u, w \in N, v \in V, u \neq w$	Binary decision variable equal to one if vehicle *v* travels from activity u to w and zero otherwise;
$T_u, u \in P$	The time at which participation in activity *u* begins;
$T_0^v, T_{2(n+IV)+1}^v$	The time at which vehicle v first departs from home and last returns to home, respectively;
$Y_u, u \in P$	The total accumulation of demand or loads (activities) immediately following the completion of activity *u*;

A generalized cost or disutility function representing costs for households is minimized with respect to a set of constraints that capture the space-time constraints of activities that need to be performed. The formulation presented as follows:

$$\text{Minimize } Z = \text{Household Travel Disutility} \tag{1}$$

Subject to:

$$\sum_{v \in V} \sum_{w \in N} X_{uw}^{v} = 1, u \in \bar{P}^{+} \tag{2}$$

$$\sum_{w \in N} X_{uw}^{v} - \sum_{w \in N} X_{wu}^{v} = 0, u \in P, v \in V \tag{3}$$

$$\sum_{w \in \bar{P}^{+}} X_{0,w}^{v} = 1, v \in V \tag{4}$$

$$\sum_{u \in \bar{P}^{-}} X_{u,2(n+IV)+1}^{v} = 1, v \in V \tag{5}$$

$$\sum_{w \in N} X_{uw}^{v} - \sum_{w \in N} X_{w,u+(n+IV)}^{v} = 0, u \in \bar{P}^{+}, v \in V \tag{6}$$

$$T_u + s_u + t_{u,(n+IV)+u} \leq T_{(n+IV)+u}, u \in P \tag{7}$$

$$X_{uw}^{v} = 1 \Rightarrow T_u + s_u + t_{uw} \leq T_w, u, w \in P, v \in V \tag{8}$$

$$X_{0,w}^{v} = 1 \Rightarrow T_0 + t_{0,w} \leq T_w, u, w \in P, v \in V \tag{9}$$

$$X_{u,2(n+IV)+1}^{v} = 1 \Rightarrow T_u + t_{u,2(n+IV)+1} \leq T_w, u, w \in P, v \in V \tag{10}$$

Constraints 2-10 are identical to those in the original HAPP formulation (*1*) with updated node sets to accommodate in-vehicle activities. Constraints 2-6 form a multi-commodity minimum cost flow problem. Constraint 7 forces node u (pick-up) to be visited before node $(n + IV) + u$ (drop-off). Constraints 8-10 describe the compatibility between routes and schedules.

2.3 Solving the Household VRP

Solving the Household VRP: Given this definition of the VRP faced by households, solving this class of problems is known to be NP-hard, indicating that the computational time to reach a solution increases infeasibly as the size of the problem increases. A set of VRP heuristics were used to feasibly solve the Household VRPs in the analysis sample. Heuristics used in this study include: (a) Clark-Wright Savings (CW) and (b) the Node Insertion family (N1, N2, N3) of heuristics (Solomon 1987). Each heuristic and their assumed set of parameter values result in solutions that favor different metrics, such as vehicle travel time and idle time. A comparison of these heuristics was completed. Table 2 provides a description of the heuristics used in this study. Table two provides the set of parameters used.

Heuristic	Description
Clark-Wright Savings (CW)	Initialize with each activity in its own tour; Combine tours to give the largest savings in Cost (Distance or Travel Time)
Node Insertion 1 (N1)	Insert Nodes to Maximize Savings from Servicing each Activity Individually (**similar to C-W Savings**)
Node Insertion 2 (N2)	Insert Nodes to Minimize Total Route Distance and Time (Both)
Node Insertion 3 (N3)	Similar to Node Insertion 1; **Account for Schedule Urgency**

Table 2: VRP Heuristics Considered

Heuristic Type ID	Heuristic Name	Parameter Values
11	Clark-Wright Savings (CW)	$\mu = 1.0$
12	Clark-Wright Savings (CW)	$\mu = 0.2$
1	Node Insertion 1 (N1)	$\mu = 1.0$; $\lambda=1.0$; $\alpha1=1.0$; $\alpha2=0$
2	Node Insertion 1 (N1)	$\mu = 1.0$; $\lambda=2.0$; $\alpha1=1.0$; $\alpha2=0$
3	Node Insertion 1 (N1)	$\mu = 1.0$; $\lambda=1.0$; $\alpha1=0$; $\alpha2=1.0$
4	Node Insertion 1 (N1)	$\mu = 1.0$; $\lambda=2.0$; $\alpha1=0$; $\alpha2=1.0$
5	Node Insertion 2 (N2)	$\mu = 1.0$; $\alpha1=0.5$; $\alpha2=0.5$; $\beta1=0.5$; $\beta2=0.5$
6	Node Insertion 2 (N2)	$\mu = 1.0$; $\alpha1=1.0$; $\alpha2=0.0$; $\beta1=0.5$; $\beta2=0.5$
7	Node Insertion 2 (N2)	$\mu = 1.0$; $\alpha1=0$; $\alpha2=1.0$; $\beta1=1.0$; $\beta2=0$
8	Node Insertion 3 (N3)	$\mu = 1.0$; $\alpha1=0.5$; $\alpha2=0.5$; $\alpha3=0$
9	Node Insertion 3 (N3)	$\mu = 1.0$; $\alpha1=0.4$; $\alpha2=0.4$; $\alpha3=0.2$
10	Node Insertion 3 (N3)	$\mu = 1.0$; $\alpha1=0$; $\alpha2=1.0$; $\alpha3=0$

Table 3: VRP Heuristics Considered – Parameter Values Used

While other heuristics could also have been used, these two sets of heuristics were used due to their performance as documented in Solomon (1987). The results from previous studies indicate that Node Insertion 1 (N1) performed the best out of all the Node Insertion heuristics.

3.0 Results and Discussion

This section presents the results of the analysis, including a discussion on implications. The next section describes the data preparation required, beginning with the 2012 Oahu Household Travel Survey to obtain the analysis sample.

3.1 Analysis Sample Preparation

This study is concerned with the impact of AVs on households. However, we address the adoption of AVs in only a limited manner. The analysis begins with the 2012 Oahu Household Travel Survey, which has 4,002 households. For this analysis we only consider households observed with vehicle-based travel patterns. Example patterns include households that carpool to work and those that drive to an express bus route and take the rest of the journey on express bus. The motivation is that households who regularly use vehicles are more likely to incorporate AVs into their household patterns when they become available. This resulted in 2,976 households being considered in our analysis of VRP Heuristics. A summary of these samples is provided below in Table 4.

Two alternative assumptions also considered on how to prepare the sample of households who would adopt and incorporate AVs in their travel-activity patterns would be (a) assuming all households will replace their current travel modes with AVs or (b) a proportion of households based on a decision mechanisms or stated-preference survey. Neither of these options were feasible given the scope of this project. Alternative (a) was infeasible because assuming all households will eventually use an AV in the future is extremely unlikely and unrealistic. Alternative (b), while appealing, would require more resources and effort to implement. Additionally, validating Alternative (b) would be extremely difficult. Therefore, the assumption that households observed to use vehicles in their observed patterns from the Oahu Survey was used.

3.1.1 HART System Scenarios

Given the interest in the HART rail system, a second analysis sample consisting of households that used vehicles in their observed patterns and used one of the express bus lines from TheBus, were assumed to be a targe market segment for HART, when it opens. Assessing the ridership for HART is not an easy task; at the time of this study, HART was not open yet and there is no data on its ridership. If we require an additional level of assessment to also identify households likely to use HART, this further complicates the assessment. Therefore, analysis on the presence of the HART system and AVs was limited to considering households who used vehicles in their observed patterns and the express bus services; this was 56 households in total.

3.2 Comparison of Heuristics for the Household VRP

Given the household VRP defined by the schedule constraints derived from the Oahu Household Travel Survey and the network performance of the Oahu TDFM, heuristics were applied to solve the individual household VRPs. The results are summarized in Tables 5 and 6, which show relative differences with respect to the heuristics and their parameter value combinations. The following metrics were used to evaluate their performance:

A) *Number of Vehicles required to Complete the Activity Schedule (#vehicles)*: The number of vehicles required in the final solution from the heuristic; we hypothesize this would decrease relative to what households were observed to use in the survey;

B) *Total Travel Time of the Household Vehicle Fleet (mins):* The total travel time across all vehicles in the household fleet;

C) *Total Idle Time of the Household Vehicle Fleet (mins):* The total duration household vehicles were idle or "parked" during the day; and

D) *Total Duration Out-of-Home of the Household Vehicle Fleet (mins)*: The total duration vehicles spend away from the home location.

Looking at Table 5, the relative to the average performance for the heuristics were consistent with the relative performance of the heuristics reported in Solomon (1987). Overall, heuristic N1 was found to outperform N2 and N3 for Total Travel Time. However, for total vehicle idle time, N2 and N3 were relatively better.

To assess the potential improvements to households, the difference between the heuristic solutions and the observe travel-activity pattern was determined. These. A positive difference indicated the observed pattern had a metric value higher than the solution. For example, looking at Table 6(a), the first combination of parameters for N1 had a difference of 78 minutes, indicating on average household AV patterns had a little more than one hour savings relative to the observed travel-activity pattern. Looking at Table 6(a), Node Insertion Heuristic 1 (N1) and the Clarke-Wright Savings Heuristics (CW) saw positive improvements (lower travel times) on average for the total travel time of the household fleet. Node Insertion Heuristic 2 (N2) and 3 (N3) saw travel time increases, on average. All heuristics saw decreases in the number of vehicles each household required in their fleets, except for the CW heuristic. There was marginal difference between households who took the express bus and under the HART scenarios.

3.3 Assessing the Potential Impact of Autonomous Vehicles for Households

To assess the potential impacts of AVs, a regression model between the relative change in the performance metrics (A-D) from the previous section for N1 and household characteristics was estimated, including the planning district location of their residence. *Only heuristic N1 was further examined since it produced solutions with better total travel times and was comparable for total* *idle time.* The mean relative change in performance metrics between the status quo and our AV scenarios were shown in Table 6 with respect to *total travel time* and *number of vehicles*. The status quo responses are assumed to be the observed travel patterns from the 2012 Oahu Household Travel Survey. Outcomes from AV scenarios were the final solutions from each heuristic.

Looking at Tables 7(a-d), with respect to AVs, households in Wai'anae and East Honolulu potentially stand to benefit in terms of travel time savings from the non-AV context (observed travel patterns), controlling for other household characteristics. Relative to other planning districts, the average marginal improvement from households in these two planning districts have the following ranges, depending on district: Wai'anae – 13.7 to 15.2 minutes; East Honolulu – 6.7 to 9.6 minutes. These two planning districts showed consistent marginal benefits from using AVs to complete their observed set of activities. Estimation results also showed that the Ewa district had a total travel time improvement of 11.9 minutes per household under an AV context, and the Ko'olau Loa district showed an increase of 21.4 minutes, but for one set of heuristic parameters. With respect to the number of vehicles required, under the AV scenario, all heuristic solutions produced a reduction, except for solutions from the Clark-Wright Savings (CW) heuristic. One explanation is that CW heuristic does not optimize for fleet size. With respect to household characteristics, household size and number of workers consistently explained these differences, statistically.

For scenarios where the HART system was introduced [*s1(exp)*], the change in impacts from AVs was marginal and statistically insignificant. However, this was under the conservative assumption that only the 56 households observed using both a vehicle and an express bus route on TheBus system would try to incorporate HART for at least a portion of their travel chain segment in combination with an AV. To fully understand the impact of the HART station, future ridership levels, including household demographics, would need to be determined.

	2012 Oahu Household Travel Survey (N = 4002 Households)							Analysis Sample (N = 2976 Households)						
Variable	**Mean**	**Median**	**Std.Dev.**	**Min**	**25%**	**75%**	**Max**	**Mean**	**Median**	**Std.Dev.**	**Min**	**25%**	**75%**	**Max**
Household Size	2.2	2	1.2	1	1	3	10	2.4	2	1.3	1	2	3	10
Number of Employed Members	1.2	1	0.93	0	1	2	6	1.4	1	0.9	0	1	2	6
Number of Student Members	0.42	0	0.82	0	0	1	6	0.51	0	0.88	0	0	1	6
Number of Members with Driver's License	1.7	2	0.87	0	1	2	7	1.9	2	0.79	0	1	2	7
Number of Operating Vehicles	1.8	2	0.85	0	1	2	8	1.9	2	0.85	0	1	2	8
Number of Out-of-Home Activities Requiring AV	---	---	---	---	---	---	---	7.6	6	5.8	1	4	10	57
	Proportion of Sample (%)							**Proportion of Sample (%)**						
1= Less than $10,000	3.1%							1.3%						
2= $10,000 to $19,999	4.5%							1.9%						
3= $20,000 to $29,999	7.5%							4.9%						
4= $30,000 to $39,999	9.3%							7.7%						
5= $40,000 to $49,999	9.5%							9.5%						
6= $50,000 to $59,999	8.9%							9.3%						
7= $60,000 to $74,999	9.1%							9.7%						
8= $75,000 to $99,999	19.0%							22.0%						
9= $100,000 to $149,999	16.0%							20.0%						
10= $150,000 or more	7.9%							9.8%						
	Proportion of Sample (%): 2012 Oahu Survey							**Proportion of Sample (%): Analysis Sample**						
(1) Central Oahu	19.0%							21.0%						
(2) East Honolulu	6.8%							7.7%						
(3) Ewa	7.2%							7.7%						
(4) Ko'olau Loa	1.2%							1.2%						
(5) Ko'olau Poko	13.0%							14.0%						
(6) North Shore	1.7%							1.7%						
(7) PUC	47.0%							44.0%						
(8) Wai'anae	3.2%							3.0%						
TOTAL	**99%**							**100%**						

Table 4: Analysis Sample Characteristics

		NVEH	TT (min)	WT (min)	DOH (min)
Node Insertion 1	μ = 1.0; λ=1.0; α1=1.0; α2=0	1.2	78	507	584
Node Insertion 1	μ = 1.0; λ=2.0; α1=1.0; α2=0	1.2	70	512	582
Node Insertion 1	μ = 1.0; λ=1.0; α1=0; α2=1.0	1.1	75	504	579
Node Insertion 1	μ = 1.0; λ=2.0; α1=0; α2=1.0	1.1	74	504	578
Node Insertion 2	μ = 1.0; α1=0.5; α2=0.5; β1=0.5; β2=0.5	1.3	136	470	606
Node Insertion 2	μ = 1.0; α1=1.0; α2=0.0; β1=0.5; β2=0.5	1.3	136	470	606
Node Insertion 2	μ = 1.0; α1=0; α2=1.0; β1=1.0; β2=0	1.3	145	466	611
Node Insertion 3	μ = 1.0; α1=0.5; α2=0.5; α3=0	1.3	146	475	620
Node Insertion 3	μ = 1.0; α1=0.4; α2=0.4; α3=0.2	1.3	144	468	612
Node Insertion 3	μ = 1.0; α1=0; α2=1.0; α3=0	1.2	116	489	605
Clark-Wright Savings	μ = 1.0	1.9	64	817	881
Clark-Wright Savings	μ = 0.2	1.8	68	722	789

Table 5: Performance Metrics Across Heuristics – Analysis Sample

Heuristic	Parameters	S0	S0 (EXP)	S1 (EXP)
Node Insertion 1	μ = 1.0; λ=1.0; α1=1.0; α2=0	0.74	7.7	6.4
Node Insertion 1	μ = 1.0; λ=2.0; α1=1.0; α2=0	9	17	15
Node Insertion 1	μ = 1.0; λ=1.0; α1=0; α2=1.0	4	7.2	5.7
Node Insertion 1	μ = 1.0; λ=2.0; α1=0; α2=1.0	4.6	7.7	6.3
Node Insertion 2	μ = 1.0; α1=0.5; α2=0.5; β1=0.5; β2=0.5	-57	-49	-51
Node Insertion 2	μ = 1.0; α1=1.0; α2=0.0; β1=0.5; β2=0.5	-57	-49	-51
Node Insertion 2	μ = 1.0; α1=0; α2=1.0; β1=1.0; β2=0	-66	-57	-59
Node Insertion 3	μ = 1.0; α1=0.5; α2=0.5; α3=0	-67	-61	-63
Node Insertion 3	μ = 1.0; α1=0.4; α2=0.4; α3=0.2	-65	-56	-59
Node Insertion 3	μ = 1.0; α1=0; α2=1.0; α3=0	-38	-25	-28
Clark-Wright Savings	μ = 1.0	21	30	27
Clark-Wright Savings	μ = 0.2	17	22	21
Sample Size (N)		**2976**	**56**	**56**

Table 6(a): Impact of AVs on the Average Total Household Vehicle Fleet Travel Time Across Scenarios

Heuristic	Parameters	S0	S0	S1
Node Insertion 1	μ = 1.0; λ=1.0; α1=1.0; α2=0	0.28	0.45	0.45
Node Insertion 1	μ = 1.0; λ=2.0; α1=1.0; α2=0	0.29	0.38	0.38
Node Insertion 1	μ = 1.0; λ=1.0; α1=0; α2=1.0	0.34	0.51	0.51
Node Insertion 1	μ = 1.0; λ=2.0; α1=0; α2=1.0	0.34	0.49	0.49
Node Insertion 2	μ = 1.0; α1=0.5; α2=0.5; β1=0.5; β2=0.5	0.21	0.42	0.42
Node Insertion 2	μ = 1.0; α1=1.0; α2=0.0; β1=0.5; β2=0.5	0.21	0.42	0.42
Node Insertion 2	μ = 1.0; α1=0; α2=1.0; β1=1.0; β2=0	0.19	0.42	0.42
Node Insertion 3	μ = 1.0; α1=0.5; α2=0.5; α3=0	0.17	0.38	0.38
Node Insertion 3	μ = 1.0; α1=0.4; α2=0.4; α3=0.2	0.18	0.38	0.38
Node Insertion 3	μ = 1.0; α1=0; α2=1.0; α3=0	0.22	0.45	0.45
Clark-Wright Savings	μ = 1.0	-0.41	-0.32	-0.34
Clark-Wright Savings	μ = 0.2	-0.32	-0.3	-0.3
Sample Size (N)		**2976**	**56**	**56**

Table 6(b): Impact of AVs on the Average Number of Vehicles Required for Households Across Scenarios

Variable	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic
Constant	7.203	3.635	1.981	6.622	3.764	1.760	4.247	2.311	1.838
HH Size	11.942	1.150	10.384	11.602	1.151	10.079	11.728	1.141	10.275
HH Students	-3.487	1.288	-2.708	-3.122	1.292	-2.416	-3.148	1.278	-2.463
HH Workers	-6.412	1.150	-5.577	-6.160	1.151	-5.354	-6.044	1.132	-5.341
HH Licensed Drivers	-5.281	1.634	-3.232	-5.187	1.634	-3.174	-5.270	1.624	-3.245
Duration at Current Home (yrs)	-0.163	0.058	-2.800	-0.147	0.060	-2.461	-0.177	0.054	-3.297
Operational Vehicles	-4.283	1.290	-3.319	-4.436	1.293	-3.430	-4.351	1.256	-3.465
Rent (1/0)	3.683	2.434	1.513	3.913	2.451	1.597	---	---	---
Single-Family Attached Unit (1/0)	-1.691	2.940	-0.575	-1.532	2.939	-0.521	---	---	---
Multi-Family Dwelling (1/0)	-2.878	2.443	-1.178	-2.425	2.533	-0.957	---	---	---
HH Income: Less than $10,000	-2.190	7.337	-0.298	-1.313	7.331	-0.179	---	---	---
HH Income: $10,000 to $19,999	-4.199	6.353	-0.661	-4.403	6.369	-0.691	---	---	---
HH Income: $20,000 to $29,999	3.390	4.331	0.783	3.278	4.358	0.752	---	---	---
HH Income: $30,000 to $39,999	-3.871	3.949	-0.980	-3.635	3.966	-0.917	---	---	---
HH Income: $40,000 to $49,999	-4.231	3.579	-1.182	-4.469	3.603	-1.240	---	---	---
HH Income: $50,000 to $59,999	-2.170	3.532	-0.614	-1.835	3.543	-0.518	---	---	---
HH Income: $60,000 to $74,999	-1.746	3.453	-0.506	-1.593	3.458	-0.461	---	---	---
HH Income: $75,000 to $99,999	-2.560	3.023	-0.847	-2.224	3.044	-0.731	---	---	---
HH Income: $100,000 to $149,999	-6.505	2.722	-2.390	-6.378	2.730	-2.336	-5.229	2.103	-2.487
HH Income: $150,000 or more	---	---	---	---	---	---	---	---	---
Central Oahu (1/0)	---	---	---	-3.377	2.478	-1.363	---	---	---
East Honolulu (1/0)	---	---	---	8.201	3.219	2.548	9.621	3.008	3.199
Ewa (1/0)	---	---	---	5.319	3.313	1.606	---	---	---
Ko'olau Loa (1/0)	---	---	---	-8.145	7.548	-1.079	---	---	---
Ko'olau Poko (1/0)	---	---	---	-3.674	2.815	-1.305	---	---	---
North Shore (1/0)	---	---	---	-9.772	7.856	-1.244	---	---	---
Primary Urban Center (1/0)	---	---	---	---	---	---	---	---	---
Wai'anae (1/0)	---	---	---	12.726	4.453	2.858	13.749	4.286	3.208
N		2976			2976			2976	
R^2		0.07523			0.08415			0.07873	
SSE		6355906			6294542			6331812	

Table 7(a): Linear Regression of Marginal Impacts on HH Vehicle Fleet Travel Times – Type 1

Variable	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic
Constant	15.346	3.496	4.389	12.849	3.616	3.554	4.474	2.210	2.025
HH Size	10.331	1.106	9.340	10.029	1.106	9.069	9.760	0.729	13.392
HH Students	-0.732	1.239	-0.591	-0.458	1.242	-0.369	---	---	---
HH Workers	-5.299	1.106	-4.792	-5.055	1.105	-4.573	-4.731	1.078	-4.389
HH Licensed Drivers	-3.060	1.571	-1.947	-3.193	1.570	-2.034	-2.806	1.501	-1.870
Duration at Current Home (yrs)	-0.199	0.056	-3.545	-0.148	0.057	-2.590	-0.150	0.051	-2.944
Operational Vehicles	-4.112	1.241	-3.313	-4.380	1.243	-3.525	-3.375	1.205	-2.801
Rent (1/0)	0.668	2.341	0.285	1.739	2.354	0.739	---	---	---
Single-Family Attached Unit (1/0)	-1.213	2.828	-0.429	-1.046	2.823	-0.371	---	---	---
Multi-Family Dwelling (1/0)	-6.315	2.350	-2.687	-4.179	2.433	-1.718	---	---	---
HH Income: Less than $10,000	-7.062	7.057	-1.001	-7.337	7.043	-1.042	---	---	---
HH Income: $10,000 to $19,999	-8.977	6.110	-1.469	-10.928	6.119	-1.786	---	---	---
HH Income: $20,000 to $29,999	-2.484	4.165	-0.596	-3.987	4.187	-0.952	---	---	---
HH Income: $30,000 to $39,999	-8.587	3.798	-2.261	-9.444	3.810	-2.479	---	---	---
HH Income: $40,000 to $49,999	-7.654	3.442	-2.223	-9.166	3.462	-2.648	---	---	---
HH Income: $50,000 to $59,999	-4.495	3.397	-1.323	-5.262	3.404	-1.546	---	---	---
HH Income: $60,000 to $74,999	-5.216	3.321	-1.571	-5.848	3.322	-1.760	---	---	---
HH Income: $75,000 to $99,999	-3.072	2.908	-1.057	-3.905	2.924	-1.335	---	---	---
HH Income: $100,000 to $149,999	-5.466	2.618	-2.088	-6.189	2.623	-2.360	---	---	---
HH Income: $150,000 or more	---	---	---	---	---	---	---	---	---
Central Oahu (1/0)	---	---	---	2.561	2.380	1.076	---	---	---
East Honolulu (1/0)	---	---	---	7.960	3.092	2.574	8.715	2.900	3.005
Ewa (1/0)	---	---	---	12.393	3.182	3.894	11.925	2.966	4.021
Ko'olau Loa (1/0)	---	---	---	-11.637	7.252	-1.605	---	---	---
Ko'olau Poko (1/0)	---	---	---	-0.243	2.704	-0.090	---	---	---
North Shore (1/0)	---	---	---	4.352	7.548	0.577	---	---	---
Primary Urban Center (1/0)	---	---	---	---	---	---	---	---	---
Wai'anae (1/0)	---	---	---	15.909	4.278	3.719	15.154	4.122	3.677
N		2976			2976			2976	
R^2		0.08166			0.08415			0.08602	
SSE		5879397			5809308			5851441	

Table 7(b): Linear Regression of Marginal Impacts on HH Vehicle Fleet Travel Times – Type 2

Variable	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic
Constant	15.946	3.585	4.447	15.336	3.711	4.132	9.317	2.316	4.024
HH Size	10.274	1.134	9.059	9.997	1.135	8.808	9.448	0.757	12.476
HH Students	-1.594	1.270	-1.255	-1.004	1.274	-0.788	---	---	---
HH Workers	-6.669	1.134	-5.881	-6.466	1.135	-5.699	-5.949	1.114	-5.338
HH Licensed Drivers	-4.249	1.611	-2.637	-4.245	1.611	-2.635	-3.972	1.544	-2.573
Duration at Current Home (yrs)	-0.238	0.058	-4.138	-0.211	0.059	-3.593	-0.229	0.052	-4.397
Operational Vehicles	-3.767	1.273	-2.960	-4.119	1.275	-3.230	-3.614	1.240	-2.915
Rent (1/0)	1.715	2.401	0.714	2.090	2.416	0.865	---	---	---
Single-Family Attached Unit (1/0)	-0.377	2.900	-0.130	-0.107	2.898	-0.037	---	---	---
Multi-Family Dwelling (1/0)	-2.389	2.410	-0.991	-1.643	2.497	-0.658	---	---	---
HH Income: Less than $10,000	-10.784	7.237	-1.490	-10.872	7.229	-1.504	---	---	---
HH Income: $10,000 to $19,999	-10.433	6.266	-1.665	-11.702	6.280	-1.863	---	---	---
HH Income: $20,000 to $29,999	-0.998	4.271	-0.234	-2.022	4.297	-0.471	---	---	---
HH Income: $30,000 to $39,999	-9.644	3.895	-2.476	-10.124	3.911	-2.589	---	---	---
HH Income: $40,000 to $49,999	-11.063	3.530	-3.134	-11.702	3.553	-3.294	-6.443	2.917	-2.209
HH Income: $50,000 to $59,999	-5.897	3.484	-1.693	-6.109	3.494	-1.749	---	---	---
HH Income: $60,000 to $74,999	-5.997	3.405	-1.761	-6.047	3.410	-1.774	---	---	---
HH Income: $75,000 to $99,999	-5.111	2.982	-1.714	-4.967	3.002	-1.655	---	---	---
HH Income: $100,000 to $149,999	-8.137	2.685	-3.031	-8.022	2.692	-2.980	-4.021	2.095	-1.919
HH Income: $150,000 or more	---	---	---	---	---	---	---	---	---
Central Oahu (1/0)	---	---	---	-0.124	2.443	-0.051	---	---	---
East Honolulu (1/0)	---	---	---	6.561	3.174	2.067	7.941	2.967	2.676
Ewa (1/0)	---	---	---	3.828	3.266	1.172	---	---	---
Ko'olau Loa (1/0)	---	---	---	-21.174	7.443	-2.845	-21.378	7.315	-2.923
Ko'olau Poko (1/0)	---	---	---	-3.845	2.775	-1.386	---	---	---
North Shore (1/0)	---	---	---	0.698	7.747	0.090	---	---	---
Primary Urban Center (1/0)	---	---	---	---	---	---	---	---	---
Wai'anae (1/0)	---	---	---	14.566	4.391	3.317	14.351	4.227	3.395
N		2976			2976.000			2976.000	
R^2		0.0746			0.084			0.079	
SSE		6182307			6120031			6154044	

Table 7(c): Linear Regression of Marginal Impacts on HH Vehicle Fleet Travel Times – Type 3

Variable	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic	Coefficient	Std. Error	t-statistic
Constant	13.567	3.563	3.808	12.712	3.690	3.445	7.002	2.312	3.029
HH Size	10.493	1.127	9.310	10.143	1.129	8.988	9.799	0.745	13.146
HH Students	-0.630	1.262	-0.499	-0.242	1.267	-0.191	---	---	---
HH Workers	-6.552	1.127	-5.813	-6.401	1.128	-5.674	-6.106	1.107	-5.518
HH Licensed Drivers	-4.096	1.602	-2.557	-4.028	1.602	-2.514	-3.835	1.533	-2.501
Duration at Current Home (yrs)	-0.178	0.057	-3.114	-0.145	0.058	-2.484	-0.170	0.052	-3.272
Operational Vehicles	-3.913	1.265	-3.094	-4.111	1.268	-3.242	-3.247	1.227	-2.646
Rent (1/0)	1.218	2.386	0.510	1.828	2.403	0.761	---	---	---
Single-Family Attached Unit (1/0)	0.594	2.882	0.206	0.705	2.881	0.245	---	---	---
Multi-Family Dwelling (1/0)	-2.079	2.395	-0.868	-1.128	2.483	-0.454	---	---	---
HH Income: Less than $10,000	-10.761	7.192	-1.496	-10.883	7.188	-1.514	---	---	---
HH Income: $10,000 to $19,999	-10.468	6.227	-1.681	-12.021	6.244	-1.925	---	---	---
HH Income: $20,000 to $29,999	-0.916	4.245	-0.216	-2.185	4.273	-0.511	---	---	---
HH Income: $30,000 to $39,999	-8.955	3.871	-2.313	-9.622	3.888	-2.475	---	---	---
HH Income: $40,000 to $49,999	-9.759	3.508	-2.782	-10.859	3.533	-3.074	-5.918	2.905	-2.037
HH Income: $50,000 to $59,999	-4.921	3.462	-1.421	-5.433	3.474	-1.564	---	---	---
HH Income: $60,000 to $74,999	-6.249	3.384	-1.847	-6.515	3.390	-1.922	---	---	---
HH Income: $75,000 to $99,999	-4.733	2.963	-1.597	-5.083	2.985	-1.703	---	---	---
HH Income: $100,000 to $149,999	-7.937	2.668	-2.975	-8.125	2.677	-3.036	-4.057	2.082	-1.948
HH Income: $150,000 or more	---	---	---	---	---	---	---	---	---
Central Oahu (1/0)	---	---	---	0.265	2.429	0.109	---	---	---
East Honolulu (1/0)	---	---	---	5.588	3.156	1.770	6.667	3.017	2.210
Ewa (1/0)	---	---	---	6.818	3.248	2.099	---	---	---
Ko'olau Loa (1/0)	---	---	---	-11.553	7.401	-1.561	---	---	---
Ko'olau Poko (1/0)	---	---	---	-4.374	2.759	-1.585	---	---	---
North Shore (1/0)	---	---	---	2.827	7.703	0.367	---	---	---
Primary Urban Center (1/0)	---	---	---	---	---	---	---	---	---
Wai'anae (1/0)	---	---	---	15.032	4.366	3.443	14.579	4.205	3.467
N		2976			2976			2976	
R^2		0.07973			0.080			0.08114	
SSE		6106452			6050434			6097093	

Table 7(d): Linear Regression of Marginal Impacts on HH Vehicle Fleet Travel Times – Type 4

4.0 Conclusions

This study investigates the potential impacts of AVs on household vehicle fleet usage was considered. The motivation is that households which potentially see an improvement in their experience performance metrics, such as total travel time across household vehicles and total number of vehicles needed to complete a set of activities, are more likely to use AVs in the future. While the results did indicate a certain market segment of households potentially see benefits from AVs, the assumption behind these estimates requires further investigation. The impact of the HART system was minimal, but the market segment potentially affected was a conservative estimate in this study. The rail was not open at the time of this study and data on ridership was unavailable. However, given a more robust estimate for the potential market of HART, the estimates for AV and HART scenarios could be revisited.

Future work includes incorporating the results into the existing Oahu TDFM. This study provided a method to generate potential household AV patterns. Given that the Oahu TDFM relies on the synthetic generation of a population and its travel-activity patterns, integrating the two would not present a serious issues, in principle.

Acknowledgements

The authors would like to thank Poya Harirchi and Tribikram Rajaure for helping with the figure preparation and preliminary work of this study.

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