TAKING ADVANTAGE OF SELF-DRIVING VEHICLES FOR PERSONAL USE

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1 ABSTRACT

People have become used to hearing about Automated Vehicles (AVs) on the news every day, and they have become a new reality in our lives that is expected to soon disrupt our world. While most of the effort has been given to advance the technology and make the idea work, little is known about how and to what degrees they change our behavior and create new norms. Therefore, understanding the interaction of these factors, and the outcomes, becomes very important, but complicate to estimate, to brace for the impacts. For example, in the field of travel behavior, they are expected to affect traffic, Value of Time (VOT), land-use, vehicle ownership, routing.

In the absence of any data or similar experience, the best alternative to develop an understanding of the potential impacts and their extents is to conduct wide range of scenario analysis. One of the possible scenarios for the future of transportation system is Private Vehicle Ownership by all or many of the households own their AVs. Since Level 5 AVs do not need a driver, they could be sent to pick up passengers. This feature could significantly impact the transportation system and therefore needs to be investigated. In this paper, the authors develop an Mixed Integer Programming optimization model that finds the optimum number of AVs that a household needs, given their activities and schedules. It could be considered a Vehicle Routing Problem with Time Window tailored to a household with level 5 AVs and their travel needs. The model also schedules AVs' trips, while considering vehicle and ride sharing, flexibly in timing, Taxis, energy, parking, vehicle ownership, value of time, as well as charging Zero Occupancy Vehicles (ZOVs). Also, a case study with multiple scenario analysis is presented to show the importance and application of the model.

2 BACKGROUND

The world of automated or autonomous vehicles (AVs) is right around the corner, and large safety benefits and cost savings are expected. Several vehicle manufacturers (e.g. Ford, General Motor Company, Tesla and Mercedes) are shepherding breakthrough-research in the domain and change is coming. In the initial stages, AVs will not be affordable by all, owing to high technology costs and the multiple types of risks associated in the development stage. However, this and financial long-term ambitions have led many technology companies towards bringing AVs to the public in the form of a shared fleet (Lyft, Uber and Google have several testbeds in the U.S., like in California, Arizona, Pittsburgh and Austin.

It is important to note, however, that it is only a matter of time before AVs will become affordable and widely available for personal ownership. If policies related to vehicle ownership remain unchanged, studies (*1*);predict that a conservative guess still points to at least 25% of the U.S. personal fleet having AV technology by 2050. An average American household today approximately has 2.34 people and owns 1.74 vehicles (U.S. Census Bureau, 2016). However, the presence of self-driving AVs can change this dramatically. The household may be able to make all their trips with fewer cars, save on fuel and parking costs, and the drivers in the household may be able to avoid taking time off of work to ferry others. From a system perspective, however, such personally-owned AVs may add congestion to the network when driving empty constantly. Hence, in the absence of similar experiences or any data to analyze and learn, and the uncertainty around the presence of AVs, the best way to brace for the unknown future is scenario analysis to develop an understanding of the extents of potential impacts.

In this study, an optimization model is formulated to analyze how households' vehicle ownership and trip making behavior could change in the presence of AVs, while taking into account peoples flexibility in terms of time and various costs associated with their trips (such as parking fees, tax on dead-heading vehicle trips, value of time, alternative modes costs, and travel disutility). A brief literature of known work in the area is presented next, followed by explaining the model's features and the formulation of the optimization model in the next section. A case-study of the Dallas-Fort-Worth region is used and solved using the Gurobi Optimization to showcase the impact of personal AVs on travel behavior. The paper concludes with a note on directions for future studies and ways to improve the analysis.

3 Literature Review

There are many studies on Vehicle Routing Problem (VRP) formulation and solution, which mostly focus on logistic type of VRP (*2*),(*3*),(*4*),(*5*). These kinds of problems are usually looked at from a logistic point of view, and significantly linked to the existence of a depo and serving customers from the depot. Their size of the problem are usually large and very time consuming to solve. Many variety of VRP problems have been defined and solved over the years and various exact, heuristic(*3*, *6*) and meta heuristics(*7*, *8*) algorithms have been proposed to solve them or improve runtime performance. Capacitated VRP(*9*, *10*), Dynamic VRP(*11*, *12*), VRP with time window(*2*, *13*), VRP with multiple trips(*14–16*), pick-up and delivery problem(*17–20*), and Dial-a-Ride transport(*21–23*), are a few examples of VRP problem types.

However, in the field of Operation Research, not many researchers have ventured into studying VRP in the context of personally-owned AVs. The authors developed an optimization algorithm for Intra-household vehicle sharing problem which was used to analyze the household in the Chicago travel tracker survey of 2009 and their daily trips. They estimated the number of households who could rely on just one AV and analyzed other households and their unserved trips(*24*). More advanced algorithm was implemented by Correia and Arem (*25*) as part of their research in which they developed a cost-minimization trip assignment model which considered Vehicle Kilometer Traveled, public transit and parking cost (any trip not served by AV were assumed to use public transit). Shared fleet management services are also being studied by many OR specialists(*26–28*).

On the other hand, in the field of transportation and travel behavior, much of the efforts on quantifying the impact of AVs have been devoted to use of stated preference surveys to analyze vehicle ownership and impact on transportation(*29–32*). Practitioners also have tried to use existing travel demand models, while improving network level of service or reducing value of time, to quantify the impacts (*33–35*). Others tried to analyze the impact of induced demand generated by traditionally disadvantaged groups (*36*, *37*). Schoettle and Sivak (*38*) looked into National Household Travel Survey (NHTS) data and investigated trip overlaps and potentials for vehicle sharing, while ignoring the travel times between activity locations. The model presented in this study builds upon previous work by authors which was mentioned above. Instead of trying to serve household trips with one AV, the model assigns a vehicle to every household trip, while optimizing a generalized cost.

4 Model Specification

Given a household's daily trips, the purpose of the presented model is to find the optimum number of AVs for the household and schedule their movements (Figure 1). The model is formulated as a Mixed Integer Programming (MIP) problem which tries to minimize a generalized cost. Different features have been included in the model to make the scenario more realistic for privately-owned AV scenario analysis:

- AVs are assumed to be level 5. That is, they could drive by their own and are able to pick up passengers without a driver.
- In addition to vehicle sharing, ride sharing is also modeled.
- Cost of travel between every origin and destination is considered as a function of distance or time.
- Cost of parking at activity locations is taken into account as a function of parking time.
- Parking at home is considered to be free.
- AVs could drive home to park there, instead of parking at activity locations, if it minimizes the generalized cost. The cost of travel to parking and return from parking is also considered.

- To increase their chance of vehicle and ride sharing, hence reducing costs, household members are willing to be flexible in terms of start time and duration of their activities.
- It is assumed that people value execution of their activities as they were planned, therefore a cost is associated with any schedule modification as a function of changed time.
- Taxis are available to serve people, and their costs as a function of time (plus a fixed cost) is added to the total cost.
- If mode of a trip has been determined in advance to be other than AV or Taxi (e.g. walk, bike or public transit), the model will accommodate the decision.
- Vehicle ownership, as a fixed value for each car, is also added to the objective function.
- It is widely expected that if AVs are not regulated they will be widely used in ZOV mode (to serve different purposes, e.g. pick up other passengers, used for shipping, or drive around instead of paying for parking). This could potentially disrupt traffic and significantly increase energy use. One policy that could limit this behavior is levying a tax on ZOVs. Therefore, a ZOV cost has been added to the objective function of this model to address this concern.
- AVs do not have to start their first trip at home. Their first trip could be any intermediate activity of the day. However, their first origin, and last destination is considered to be home.
- Feasibility of trips in terms of travel times are guaranteed. Time dependent travel times are used in enforcing the feasibilities.
- The model does not apply capacity limit to the vehicles. It needs to be emphasized that the model is for regional demand analysis rather than operation, hence it is assumed that the right size of AVs have been purchased by households, which is rational assumption.

Figure 1 depicts a household with two members and their daily activities' schedule (the thick bars), and the result of the model. According to the optimization model, this household is better off owning just one AV (green lines), given their preferences and costs. The narrow bars show how one member (person 2) should change her schedule to share the first ride with person 1, and the arrows depict the AV's travel plan to pick up and drop off household members. The dash lines represent ZOV trips and blue bars indicate home-based activities. It should be mentioned that since walk has been chosen as the mode of two trips (exogenous information), the model does not allocate AV or Taxi to those trips.

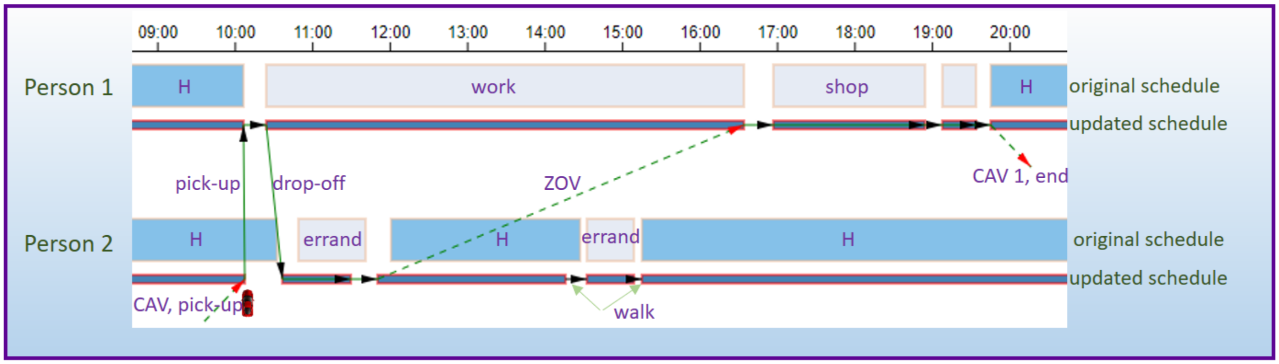

Figure 1- A two persons household, their daily activities and trips

5 FORMULATION

The trip decisions of privately-owned AVs while catering to the household's daily activities based on different cost parameters and constraints is formulated as a cost-minimization Mixed Integer Programming problem. Following input data, the decision variables, constraints and finally the objective function is explained.

Two nodes have been defined for each activity, one for the start of the activity and one for the end.

5.1 Problem Data

Since the model is formulated at household level, their activities start and duration, and travel times between every combination of activities at planned or estimated departure time is needed. The data need to solve the problem is information for a household, H which includes a set of people, P_h. All activities made by each person $i \in P_h$ is denoted by A_i. Individual activity a is denoted by $A_{i,a} \in A_i$, for each person $i \in P_h$. For each activity, two nodes have been defined, start and end of activity, where $A_{i,a,s}$ is the start node and $A_{i,a,e}$ is the end node. $s_{i,a}$ and $e_{i,a}$ are planned start and planned end time and $\mathrm{d_{i,a}} = \mathrm{e_{i,a}} - \mathrm{s_{i,a}}$ is the planned duration of the activity.

Also $S_{i,a}$ and $D_{i,a}$ respectively denote the start and end time thresholds of $A_{i,a}$ and $H_{i,a}$ is a binary value indicating whether the activity $A_{i,a}$ is home activity. V is the maximum number of vehicles in a household.

${}^{A_{i,a,e}}_{Home}R_v$ and ${}^{A_{i,a,e}}_{Prk_{A_{j,b,s}}}R_v$ represent the travel time from home/parking to node $A_{i,a,e}$ by vehicle v at time $e_{i,a} - {}^{A_{i,a,e}}_{Home}R_v(at\ time\ e_{i,a})$. Similarly, ${}^{Prk}_{A_{i,a,s}}R_v$ and ${}^{Home}_{A_{i,a,s}}R_v$ represent the travel time from node $A_{i,a,s}$ to parking/home at time $s_{i,a}$ by vehicle v. Also ${}^{A_{j,b,n}}_{A_{i,a,m}}R_v$ denotes the travel time from origin node $A_{i,a,m}$ to destination node $A_{j,b,n}$ at time t, where $m, n \in \{s, e\}$ and t=s_a where $\mathrm{m} =$ s and $t = e_{i,a}$ $where\ m =$ e experienced on vehicle $v \in V_h$.

5.2 Decision Variables

If a vehicle travels to the start node of an activity, its sole purpose is to drop off related passenger, and if it travels to end node of an activity, it is solely to pick up the related passenger.

It is also assumed that a vehicle with passenger is not allowed to travel to parking. Also, v=0 is reserved for taxi trips and trips that will be executed by other modes (e.g. determined by ABM).

Linear variables are used to denote the optimal start time, duration and end time of an activity "a", $\boldsymbol{\sigma_{i,a}}$ *and* $\boldsymbol{\delta_{i,a}}$ respectively.

Term ${}_{A_{i,a,m}}^{A_{j,b,n}}T_v$ is a binary variable representing vehicle choice/mode, a trip from node $A_{i,a,m}$ to node $A_{j,b,n}$ by vehicle v. That is, ${}_{A_{i,a,e}}^{A_{j,b,n}}T_v$=1 implies that vehicle v has picked up person "i" from end node $A_{i,a,e}$ and is being taken to node$A_{j,b,n}$. Also ${}_{A_{i,a,s}}^{A_{j,b,n}}T_v = 1$ indicates that person "i" has been dropped off at start node$A_{i,a,s}$ and the vehicle has left for node$A_{j,b,n}$.

Variable ${}_{A_{i,a,e}}^{A_{i,a+1,s}}T_v, a|a, a+1 \in \mathrm{A}_i, v|v > 0$ represent a trip made by person "i" from activity "a" to her next activity "a+1" by vehicle "v" and ${}_{A_{i,a,s}}^{A_{i,a,e}}T_v$ represent vehicle v parking at the activity location "a". Similarly, ${}_{A_{i,a,s}}^{Home}T_v$ and ${}_{A_{i,a,s}}^{Prk}T_v$ represent trips from node $A_{i,a,s}$ to home/parking and ${}_{Home}^{A_{i,a,\mathrm{e}}}T_v$ represent trip from Home to node $A_{i,a,\mathrm{e}}$ by vehicle "v" for a pickup. Variable ${}_{Prk_{A_{j,\mathrm{b,s}}}}^{A_{i,\mathrm{a,e}}}T_v$ also indicates the same, however it also implies before the pickup, the vehicle should have gone to the parking from node $A_{j,\mathrm{b,s}}$ (after dropping off person j at activity location b).

To be able to levy a tax on Zero Occupancy Vehicles, their trips should be identified. Following to the definition of ${}_{A_{i,a,m}}^{A_{j,b,n}}T_v$, it is already known that vehicle "v" always carries passengers where m=e (somebody has just been picked up), or when n=s (somebody is being dropped-off). Also, when a trip is made to/from parking, or to/from home, they are ZOV trips. The only type of travel that needs to be investigated for ZOV is ${}_{A_{i,a,s}}^{A_{j,b,e}}T_v$, where a person has just been dropped off, and the vehicle is planning to pick another person up. Therefor a new binary variable is defined to identify ZOV trips:${}_{A_{i,a,s}}^{A_{j,b,e}}Z_v$. Also, a series of supporting variables are defined to be used to set the variable to true or false, ${}_{A_{i,a,s}}^{A_{j,b,e}}Y_v^{A_{k,c,s}}$. This variable indicates whether or not vehicle "v" traveling from start node of activity "a" to end node of activity "b" carries passenger "k" leaving activity location "c" to go to activity "c+1" location, Figure 2:

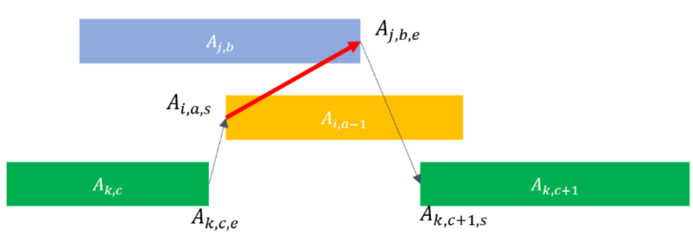

Figure 2- Demonstrating the movements and the approach used for identifying ZOV trips

Obviously many of the trips are invalid or infeasible due to time and trip purpose (pick up, drop off) restrictions, which will be eliminated when constraints are applied) however, when generating ${}^{A_{j,b,n}}_{A_{i,a,m}}T_v$ variables, the following rules are applied to eliminate obvious infeasible/invalid trips. This will reduce the size of the problem, hence boost the performance.

- Travel from the start of the first activity is invalid: $m = s \rightarrow a | a - 1 \in \mathrm{A}_i$
- Travel to the start of the first activity is invalid: $n = s \rightarrow b | b - 1 \in \mathrm{A}_j$
- Travel from the end of last activity is invalid: $m = e \rightarrow a | a + 1 \in \mathrm{A}_i$
- Travel to the end of last activity is invalid: $n = e \rightarrow b | b + 1 \in \mathrm{A}_j$
- When traveling from the start of an activity (after a drop off) to the start of another activity (to drop off), the difference between lower bound of the start of the origin activity, and upper bound of the start of the destination activity, should be at least equal or greater than the travel time between the two locations:

$$m = s, n = s \rightarrow s_{i,a} - S_{i,a} + {}^{A_{j,b,s}}_{A_{i,a,s}}R_v \leq s_{j,b} + S_{j,b} \tag{1}$$

- Similarly, for travels from start of an activity to the end of another activity, there should be enough time between the lower bound of the start of the origin activity, and upper bound of the end of the destination activity to travel between activities' locations:

$$m = s, n = e \rightarrow s_{i,a} - S_{i,a} + {}^{A_{j,b,e}}_{A_{i,a,s}}R_v \leq s_{j,b} + S_{j,b} + d^h_{A_{i,a}} + D_{j,b} \tag{2}$$

- Same logic applies to trips from end of an activity to the start or end of other activities (3) and (4) and also pick up trips when the vehicles is parked at parking (5):

$$m = e, n = s \rightarrow s_{i,a} - S_{i,a} + d^h_{A_{i,a}} - D_{i,a} + {}^{A_{j,b,s}}_{A_{i,a,s}}R_v < s_{j,b} + S_{j,b} \tag{3}$$

$$m = e, n = e \rightarrow s_{i,a} - S_{i,a} + d_{i,a} - D_{i,a} + {}^{A_{j,b,s}}_{A_{i,a,s}}R_v < s_{j,b} + S_{j,b} + d_{j,b} + D_{j,b} \tag{4}$$

$$\begin{aligned} &{}^{A_{i,a,e}}_{Prk_{A_{j,b,s}}}T_v, a|a+1 \in \mathrm{A}_i, b|b-1 \in \mathrm{A}_j, i = j \rightarrow s_{i,a} > s_{i,b}, v|v > 0, \\ &b, a|\, s_{j,b} - S_{j,b} + {}^{Prk}_{A_{j,b,s}}R_v + {}^{A_{i,a,e}}_{Prk_{A_{j,b,s}}}R_v < s_{i,a} + S_{i,a} + d_{i,a} + D_{i,a} \end{aligned} \tag{5}$$

- For each person only travels between two consecutive activities are permitted. For example, a person cannot travel from her first activity, to her third activity. Only travel to the second activity is defined:

$$i = j \rightarrow b|\, b = a + 1, m|m = e, n|n = s \tag{6}$$

- Taxi sharing is not modeled in this study so Taxi trips from one person's location to another person's location is not permitted:

$$i \neq j \rightarrow v|v > 0 \tag{7}$$

5.3 Constraints

- It is assumed that people are willing to be flexible to be able to take advantage of vehicle and ride sharing, however this flexibility should be reasonable. Therefore, we have constrained the start and duration of activities to a certain limit (which could be modeled or assumed). The delta change in start times and durations is represented by,

$$\left|\boldsymbol{\sigma}_{i,a} - s_{i,a}\right| \leq S_{i,a}, \ \forall i \in \mathrm{P_h}, \forall a \in \mathrm{A}_i \tag{8}$$

$$\left|\boldsymbol{\delta}_{i,a} - d_{i,a}\right| \le D_{i,a},\ \ \forall\, i \in \mathrm{P_h},\ \forall a \in \mathrm{A}_i \tag{9}$$

- The maximum number of vehicles used in the model is limited by maximum number of vehicles the household owns. The maximum number could be derived from a vehicle ownership model or just be set to a fixed number (e.g. household size).

$$v \le \mathrm{V}_h \tag{10}$$

- A vehicle can enter and exit the network (i.e., leave home or get back home) at most once. This is imposed so that the multiple trips to home during the duration of a person's activity is eliminated. Another check is included to ensure that the vehicle cannot exit the network without having entered the network in the first place.

$$\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{A_{i,a,e}}_{Home}T_v \le 1, \qquad \forall\, v{:}\ 0 < v \le V_h \tag{11}$$

$$\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{Home}_{A_{i,a,s}}T_v \le 1, \qquad \forall\, v{:}\ 0 < v \le V_h \tag{12}$$

$$\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{A_{i,a,e}}_{Home}T_v = \sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{Home}_{A_{i,a,s}}T_v\,, \qquad \forall\, v{:}\ 0 < v \le V_h \tag{13}$$

- Conditions from the VRPs for passenger pickup and drop-off are included. Every person in the household must be catered to, i.e., every person should be picked and dropped off to perform their activities throughout the day. Additionally, the vehicle that picks up a person should be the one to drop them off.

$$\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{v=0}^{V}\sum_{m=\{s,e\}} {}^{A_{j,b,m}}_{A_{i,a,e}}T_v = 1 \tag{14}$$
$$\forall\, i \in \mathrm{P_h},\ \forall a|a+1 \in \mathrm{A}_i\,, m \in \{s,e\}$$

$$\sum_{j}^{j\in P_h}\sum_{b}^{A_j}\sum_{v=0}^{V}\sum_{m=\{s,e\}} {}^{A_{i,a,s}}_{A_{j,b,m}}T_v = 1 \tag{15}$$
$$\forall i \in \mathrm{P_h},\ \forall a|a-1 \in \mathrm{A}_i\,, m \in \{s,e\}$$

$$\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}} {}^{A_{j,b,m}}_{A_{i,a,e}}T_v = \sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}} {}^{A_{i,a+1,s}}_{A_{j,b,m}}T_v \tag{16}$$
$$\forall i \in P,\ \forall a, a+1 \in A_i\,, m \in \{s,e\}\ \forall\ 0 < v \le V$$

- This VRP must be checked for temporal consistency. The vehicle must have arrived at the pickup location before the person can be picked up.

$$\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j} {}^{A_{i,a,e}}_{Prk_{A_{j,b,s}}}T_v + {}^{A_{i,a,e}}_{Home}T_v + \sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}} {}^{A_{i,a,e}}_{A_{j,b,m}}T_v = \tag{17}$$

$$\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}}^{e} {}_{A_{i,a,e}}^{A_{j,b,m}}T_v \;\; \forall i \in \text{P},\ \forall a, a+1 \in \text{A}_i\ , m \in \{s,e\}\ \forall\ 0 < v \leq V$$

- Once the vehicle drops the person off, it must leave the location or park at the activity location.

$$\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j} {}_{A_{i,a,s}}^{Prk}T_v + {}_{A_{i,a,s}}^{Home}T_v + \sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}} {}_{A_{i,a,s}}^{A_{j,b,m}}T_v = \sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}} {}_{A_{j,b,m}}^{A_{i,a,s}}T_v \qquad (18)$$
$$\forall i \in P,\ \forall a, a-1 \in A_i\ , m \in \{s,e\}\ \forall\ 0 < v \leq V$$

- The binary trip variable from parking location to pick up location can be 1 only if the vehicle had previously traveled to the parking location.

$${}_{A_{i,a,s}}^{Prk}T_v = \sum_{j}^{j\in P_h}\sum_{b}^{b} {}_{Prk_{A_{i,a,s}}}^{A_{j,b,e}}T_v \quad \forall i \in \text{P},\ \forall a \in \text{A}_i\ ,\ \forall\ 0 < v \leq V \qquad (19)$$

- A trip may be made only if the travel time between activity locations conform with the start and end times of the activities. In case of a drop off trip, the arrival time should be earlier than the start time of the activity but not too soon (for example within one minute of the start time)(20). In the case of pick up, the vehicle is allowed to arrive any time before the activity end time if it did not already pick up a passenger (22). If it arrives earlier, the vehicle may incur parking cost for the duration of stay if it is not a home activity. Additionally, for the case of traveling from parking for a pick up, travel times to and from the parking should also be taken into account in addition to the activities timings (24).

${}_{A_{i,a,s}}^{A_{j,b,s}}T_v = 1 \rightarrow \boldsymbol{\sigma}_{j,b} - 1 \leq \boldsymbol{\sigma}_{i,a} + {}_{A_{i,a,s}}^{A_{j,b,s}}R_v \leq \boldsymbol{\sigma}_{j,b}$, $\forall\ 0 < v \leq V, \forall i,j \in \text{P},\ \forall a \in \text{A}_i, \forall b \in \text{A}_j$	Drop-off, after another drop-off	(20)
${}_{A_{i,a,e}}^{A_{j,b,s}}T_v = 1 \rightarrow \boldsymbol{\sigma}_{j,b} \leq \boldsymbol{\varepsilon}_{i,a} + {}_{A_{i,a,e}}^{A_{j,b,s}}R_v \leq \boldsymbol{\sigma}_{j,b}$, $\forall\ 0 < v \leq V, \forall i,j \in \text{P},\ \forall a \in \text{A}_i, \forall b \in \text{A}_j$	Drop-off, after a pickup	(21)
${}_{A_{i,a,s}}^{A_{j,b,e}}T_v = 1 \rightarrow \boldsymbol{\sigma}_{i,a} + {}_{A_{i,a,s}}^{A_{j,b,e}}R_v \leq \boldsymbol{\varepsilon}_{j,b}$, $\forall\ 0 < v \leq V, \forall i,j \in \text{P},\ \forall a \in \text{A}_i, \forall b \in \text{A}_j$	Pickup, after a drop off	(22)
${}_{A_{i,a,e}}^{A_{j,b,e}}T_v = 1 \rightarrow \boldsymbol{\varepsilon}_{j,b} - 1 < \boldsymbol{\varepsilon}_{i,a} + {}_{A_{i,a,e}}^{A_{j,b,e}}R_v \leq \boldsymbol{\varepsilon}_{j,b}$, $\forall\ 0 < v \leq V, \forall i,j \in \text{P},\ \forall a \in \text{A}_i, \forall b \in \text{A}_j$	Pickup, after a pickup	(23)
$\boldsymbol{\sigma}_{i,a} + {}_{A_{i,a,s}}^{Prk}R_v + {}_{Prk_{i,a,s}}^{A_{j,b,e}}R_v \leq \boldsymbol{\varepsilon}_{j,b}$, $\forall\ 0 < v \leq V, \forall i,j \in \text{P},\ \forall a \in \text{A}_i, \forall b \in \text{A}_j$	Pickup, travel from parking	(24)

- To prevent a loop trip (could be an issue when more than one individual is at one location), round trip travel between two activities are prohibited.

$${}_{A_{i,a,m}}^{A_{j,b,n}}T_v + {}_{A_{j,b,n}}^{A_{i,a,m}}T_v \leq 1\ \forall i,j \in \text{P}, \forall a \in \text{A}_{i,}, \forall b \in \text{A}_j\ , m,n \in \{s,e\}\ \forall\ 0 < v \leq V \qquad (25)$$

- To further clarify the variables, it should be mentioned that when a trip starts from a start-node, it means that a person has just been dropped off, which implies an activity must have existed before the drop off location activity: ${}_{A_{i,a,m}}^{A_{j,b,n}}T_v$:

$$m = s \rightarrow a|a - 1 \in A_i \quad (26)$$

and similarly:

$$n = s \rightarrow \ b|b - 1 \in A_j \quad (27)$$

$$m = e \rightarrow a|a + 1 \in A_i \quad (28)$$

$$n = e \rightarrow \ b|b + 1 \in A_j \quad (29)$$

- To determine if passengers exist on a trip by vehicle v when traveling between $\boldsymbol{A_{i,a,s}}$ and $\boldsymbol{A_{j,b,e}}$, all other intra-personal trips, ${}_{\boldsymbol{A_{k,c,e}}}^{\boldsymbol{A_{k,c+1,e}}}\boldsymbol{T_v}$, are investigated to see they met the following constraints (Figure 2):
  - Whether the trip timing allows the ride share **Error! Reference source not found.Error! Reference source not found.**
  - No direct trip between $\boldsymbol{A_{k,c,e}}$ and $\boldsymbol{A_{k,c+1,e}}$ took place, **Error! Reference source not found.**
  - Passenger k was picked up by vehicle v from node $\boldsymbol{A_{k,c,e}}$ **Error! Reference source not found.**

$$\boldsymbol{\varepsilon}_{k,c} + {}_{A_{k,c,e}}^{A_{i,a,s}}R_v \leq \boldsymbol{\sigma}_{i,a} \quad (30)$$

$$\boldsymbol{\varepsilon}_{j,b} + {}_{A_{j,b,e}}^{A_{k,c+1,s}}R_v \leq \boldsymbol{\sigma}_{k,c+1} \quad (31)$$

$$\sum^{l}\sum^{f}\sum^{m} {}_{A_{k,c,e}}^{A_{l,f,m}}T_v = 1 \quad (32) \qquad \rightarrow {}_{A_{i,a,s}}^{A_{j,b,e}}Y_v^{A_{k,c,s}} = 1$$

$$ {}_{A_{k,c,e}}^{A_{k,c+1,s}}T_v = 0 \quad (33)$$

$\forall\ 0 < v \leq V,\ \ \forall i,j,k \in \mathrm{P}, \mathrm{i} \neq \mathrm{j} \neq \mathrm{k}, \forall a \in \mathrm{A}_i, \forall b \in \mathrm{A}_j, \forall c \in \mathrm{A}_k,\ \ a|a-1 \in \mathrm{A}_i,\ \ b|b+1 \in \mathrm{A}_j,$
$c|c+1 \in \mathrm{A}_k,\ \ m \in \{s, e\}$

Then if the following criteria were met, the trip is considered as ZOV:

$$\sum^{k}\sum^{c} {}_{A_{i,a,s}}^{A_{j,b,e}}Y_v^{A_{k,c,s}} = 0 \quad (34) \qquad \rightarrow {}_{A_{i,a,s}}^{A_{j,b,e}}Z_v = 1$$

$$ {}_{A_{i,a,s}}^{A_{j,b,e}}T_v = 1 \quad (35)$$

$a, b|\ {}_{A_{i,a,s}}^{A_{j,b,e}}R_v > 0\ , \forall\ 0 < v \leq V, \forall i,j,k \in \mathrm{P}, i \neq j \neq k, \forall a \in \mathrm{A}_i, b \in \mathrm{A}_j, c \in \mathrm{A}_k$
$\mathrm{c}|\ \mathrm{c}+1 \in \mathrm{A}_k, s_{k,c+1} + S_{k.c+1} \geq\ s_{j,b} - S_{j,b} + d_{j,b} - D_{j,b}$

5.4 Objective Function for Cost Minimization

The objective function is the sum of ten distinct components:

1. It is assumed that people associate a negative cost to any changes to their planned activities, therefore in this model these changes are penalized, and the model is formulated to minimize the associated cost and stay close to original schedule.

$$\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i}\left(\left|\boldsymbol{\sigma}_{i,a} - s_{i,a}\right| + \left|\boldsymbol{\delta}_{i,a} - d_{i,a}\right|\right) * Cost_{Time} \tag{22}$$

2. The fuel costs incurred from making a trip by AVs is also added to the general cost, as a function of the trip travel time (could be replaced by VMT)

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i}\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j}\sum_{m=\{s,e\}}\sum_{n=\{s,e\}} {}^{A_{j,b,n}}_{A_{i,a,m}}T_v * \left(Cost_{Fuel} * {}^{A_{j,b,n}}_{A_{i,a,m}}R_v\right) \tag{23}$$

3. The cost of Taxi is also added for all intra-personal trips

$$\sum_{i}^{i\in P_h}\sum_{a}^{a+1\in A_i} {}^{A_{i,a+1,s}}_{A_{i,a,e}}T_v * \left(Cost_{Taxi-Fixed} + Cost_{Taxi-\$/hr} * {}^{A_{i,a+1,s}}_{A_{i,a,e}}R_v\right) \tag{23}$$

4. Cost of AV ownership is included in the minimization along with fuel costs and ZOV tax for pickup trips when vehicle starts from home.

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a+1\in A_i} {}^{A_{i,a,e}}_{Home}T_v * \left(Cost_{CAV} + (Cost_{Fuel} + Cost_{ZOV-Tax}) * {}^{A_{i,a,e}}_{Home}R_v\right) \tag{24}$$

5. Similarly, fuel and ZOV tax are added to the costs for vehicles exiting the system. Obviously if the last activity a vehicle served is a home activity, this cost will be equal to zero (travel time will be equal to zero), otherwise if a vehicle leaves the network after dropping off a person it will be empty, and it will incur fuel cost to drive home.

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{Home}_{A_{i,a,s}}T_v * (Cost_{Fuel} + Cost_{ZOV-Tax}) * {}^{Home}_{A_{i,a,s}}R_v \tag{25}$$

6. Next, the fuel costs to go to the parking location after a person is dropped off at an activity location is added along with the ZOV tax associated with this travel.

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i} {}^{Prk}_{A_{i,a,s}}T_v * (Cost_{Fuel} + Cost_{ZOV-Tax}) * {}^{Prk}_{A_{i,a,s}}R_v \tag{26}$$

7. Like the previous summation, fuel costs and the ZOV tax for pickup trips from parking locations to the person's activity location is minimized.

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i}\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j} {}^{A_{i,a,e}}_{Prk_{j,b,s}}T_v * (Cost_{Fuel} + Cost_{ZOV-Tax}) * {}^{A_{i,a,e}}_{Prk_{j,b,s}}R_v \tag{27}$$

8. The ZOV trip made between two people's activity location is taxed according to following formula.

$$\sum_{v=1}^{V}\sum_{i}^{i\in P_h}\sum_{a}^{a\in A_i}\sum_{j}^{j\in P_h}\sum_{b}^{b\in A_j} {}^{A_{j,b,e}}_{A_{i,a,s}}Z_v * \left(Cost_{ZOV-Tax} * {}^{A_{j,b,e}}_{A_{i,a,s}}R_v\right) \tag{28}$$

9. The parking cost if a vehicle parks at activity location other than home:

$$\sum_{v=1}^{V} \sum_{i}^{i \in P_h} \sum_{a}^{a \in A_i} {}_{A_{i,a,s}}^{A_{i,a,e}}T_v * Cost_{Park} * \mathrm{d}_{\mathrm{i,a}} * (1 - H_{i,a}) \tag{28}$$

10. The parking cost if a vehicle arrives at an activity location for pick up earlier than the scheduled departure time, for all non home based activities. It should be mentioned that the duration of parking is estimated based on planned timing of activities, rather than optimized timing. According to the constraints, drop off trips will not endure parking time.

$$\sum_{v=1}^{V} \sum_{i}^{i \in P_h} \sum_{a}^{a \in A_i} \sum_{j}^{j \in P_h} \sum_{b}^{b \in A_j} ({}_{A_{i,a,s}}^{A_{j,b,e}}T_v \left(\mathrm{e}_{\mathrm{j,b}} - \mathrm{s}_{\mathrm{i,a}} - {}_{A_{i,a,s}}^{A_{j,b,e}}R_v \right) + {}_{A_{i,a,e}}^{A_{j,b,e}}T_v \left(\mathrm{e}_{\mathrm{j,b}} - \mathrm{e}_{\mathrm{i,a}} - {}_{A_{i,a,e}}^{A_{j,b,e}}R_v \right)) * \left(1 - H_{i,a}\right) * \left(1 - H_{j,b}\right) * Cost_{Park} \tag{28}$$

5.5 Sample Outcome

Figure 3 depicts another household's activities (with five members), with a total of 25 trips. According to the model, with specific cost and flexibility assumptions, this household could rely on two AVs for their daily trips. The green AV makes 16 trips, including 4 ZOV trips, and the yellow AV makes 5 trips, including one ZOV trip. 8 taxi trips also have been made by members. So instead of 25 trips, the household has end up making 29 trips. It should be mentioned that travels between two locations with zero travel time have been depicted in the picture with arrows (e.g. home to home), but not counted in aggregate numbers.

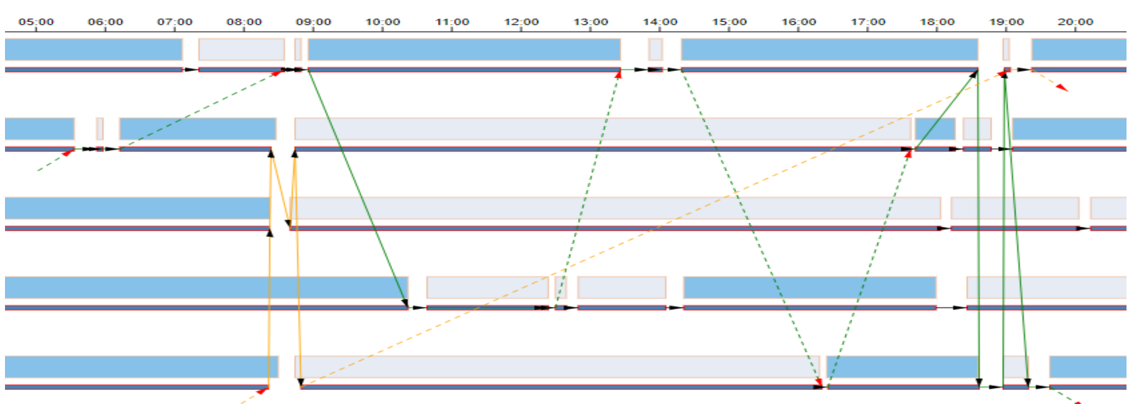

Figure 3- A sample household of size 5, their daily activities and model results

6 CASE STUDY

To demonstrate the application of the model in revealing the importance of scenario analysis of Privately Owned AVs, the North Central Texas Council of Governments' Household Travel Survey of 2009 was employed. The dataset was processed and household activities with their information were compiled. Also skim tables were used to estimate the travel times to be used in the model.

7 CONCLUSION

In this paper a Mixed Integer Programming model was developed to find the optimum number of Level 5 AVs to serve a household travel needs, while considering vehicle and ride sharing, flexibly in timing, Taxis and minimizing a generalized cost. Among the costs that is considered are energy, parking, vehicle ownership, value of time, as well as charging ZOVs.

The households in the North Central Texas Council of Governments travel survey of 2009 was used to test the model and run multiple scenarios with different cost assumptions to show the importance and application of the model.

and a visualizer was develop to visually inspect the assignments.

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