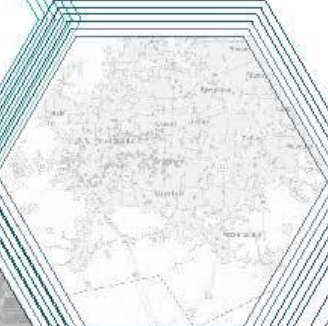




When and Where are Dedicated Lanes Needed under Mixed Traffic of Automated and Non-Automated Vehicles for Optimal System Level Benefits?

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FINAL REPORT

WHEN AND WHERE ARE DEDICATED LANES NEEDED UNDER MIXED TRAFFIC OF AUTOMATED AND NON-AUTOMATED VEHICLES FOR OPTIMAL SYSTEM LEVEL BENEFITS?

FINAL PROJECT REPORT

by

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16. Abstract Automated vehicle (AV) technology is rapidly moving towards reality and will be mature within the next decade. However, the physical, institutional, and legal infrastructure for enabling widespread adoption of this technology is still lagging significantly. The focus of this research is on developing a decision framework for optimal upgrading of the road network for mixed AV and conventional (NAV) traffic. Given that AVs will undoubtedly share a large segment of the current road network with conventional traffic for the foreseeable future, how the network can be retrofitted to optimize the flow of all traffic is a critical issue. Of interest are questions regarding when and where the provision of dedicated lanes for AVs can offer benefits for all traffic, and at what level of AV adoption this investment becomes cost-effective. Answers to these questions are critical for planning the future transportation system. We use the term autonomous vehicle to indicate that they can not only drive without human interference using sensing technology but can also communicate with other vehicles and road infrastructure. While the technology is progressing rapidly, planning infrastructure investments and enhancements to optimally harness the benefits of AV technology capabilities merits serious attention. Specifically, the use of dedicated lanes to accommodate AVs so that they may platoons is an important consideration from a policy as well as planning perspective. The proposed study investigates this issue to determine when and where dedicated AV lanes would provide the maximum benefit to all traffic and make such infrastructure investments cost effective.			
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Introduction

Traffic congestion and road safety are two important concerns for most of the planning agencies. The World Bank states that traffic congestion could cost developing economies up to 5% of their annual GDP, and between 0.5 to 3% for developed economies. The need for analyzing information about traffic conditions and devising measures to decrease highway congestion has become the focus of recent research in transportation planning. In addition to congestion, safety is an important concern for transportation planning and operation agencies. Past statistics indicated that a large fraction of fatal crashes can be attributed to driver error.

Autonomous vehicle technology has developed as the answer to the problem of highway congestion and safety, by demonstrating capabilities of sensing the environment and navigating without human intervention. Automated vehicles (AVs) are an important improvement on human-driven vehicles (referred in this paper as NAVs). AVs can use sensing technology along with the capability to communicate with other automated vehicles using vehicle to vehicle technology (V2V). They also can communicate with infrastructure using vehicle to infrastructure (V2I) technology. V2V technology helps AVs move together in the form of platoons due to their ability to synchronize operations by simultaneous braking and acceleration, thus leading to better traffic control and reduced travel costs. The optimal operation of AVs will require (i) investment for improvement in infrastructure and, (ii) conducive traffic conditions for AVs to form and move as a platoon. First, the investment in road infrastructure here implies both, improved road signage and lane markings as well as communication infrastructure. Ideally, the entire road network needs to be transformed to enable the efficient and safe operation of AVs. However, due to implementation challenges that may require road closures impacting commuting traffic and budgetary limitations, it is often not possible to commence the improvement in all the links of a road network to make it ready for AVs. Therefore, a sequential or staged improvement strategy in existing road infrastructure needs to be planned. Subset links of an existing network needs to be demarcated at different market penetration of AVs for focused investment. Second, the ideal case or most conducive traffic condition for AV operation will be achieved when all vehicles in the network are AVs with V2V and V2I capability. However, 100 percent market penetration of AVs is not possible overnight and for a considerable time after the introduction of AVs for the general public, the traffic is likely to be a mix of conventional human-driven vehicles and AVs. Under mixed traffic of AVs and NAVs, the AVs will face operational difficulties in forming platoons. An intuitive solution to this problem will be dedicating subset of links (or lanes of those links) for AVs. This will facilitate the optimal operation of AVs especially on those links and decrease their travel times. However, it may increase the congestion on other links for NAVs. Therefore, this leads to an interesting problem “when and where dedicating links for AVs are beneficial considering optimal system-level benefits under the mixed traffic of AVs and NAVs?”

This report focuses on the use of dedicated lanes to accommodate AVs for platooning and aims to determine the optimum allocation of road space that would allow system optimal operation of mixed traffic of AVs and NAVs. Specifically, the study aims to determine the optimal levels of

market penetration to demarcate links for AVs, which would lead to decreased congestion and total system travel time. As stated above, it will also allow focused investment for making the infrastructure ready for automated vehicles.

The proposed research investigates the questions stated above by integrating two methodological dimensions namely, macroscopic analysis of network flows and system level optimization strategy. These two components inform each other using a bi-level framework. The mathematical formulation of the upper and lower level is presented, and the solution algorithm is presented. Numerical experiments are conducted to demonstrate the proposed framework using a small 18 link test network. The small size network facilitates link level analysis and visualization of the numerical results.

The rest of the paper is organized as follows. The next Section presents a summary of the related work. The Section after that introduces the proposed bi-level framework for the determination of dedicated lanes, which is followed by the proposed solution algorithms to this bi-level problem. This Section includes a description of the mixed equilibrium model, along with details about the problem formulations of upper and lower levels. The section after that presents the implementation details. The next section demonstrates the numerical experiments, visualize the results, and discuss the performance of the model. Finally, the closing section presents the conclusions of the paper by summarizing the major findings and comments.

Related past work

Planning under the automated driving environment is a new area of research but it has attracted immense interest in recent past. Execution of the research framework proposed in this study entails the estimation of network flows under mixed traffic that includes both AVs and non-AVs. A suitable mixed vehicle user equilibrium model needs to be devised by enhancing state-of-the-art network assignment models. Deterministic user equilibrium (DUE) traffic assignment is a widely used technique to model network flows by mapping travel demand onto a transportation network (Beckmann et al., 1956). However, this modeling paradigm has two important deficiencies that stem from two basic underlying premises. First, it assumes that all network users have perfect knowledge of network conditions; and second, it assumes homogeneity in the perception of travel cost by network users (Sheffi, 1985). Both researchers and practitioners recognize that a network user may not have perfect knowledge of network conditions and different network users may perceive travel costs differently. Due to these properties, DUE may fail to generate network flows that match the reality (Mahmassani and Chang, 1987). To overcome these limitations, the stochastic user equilibrium (SUE) methodology, in which the above-stated assumptions are relaxed, was proposed (Daganzo and Sheffi, 1977, p. 197). Fisk (1980) developed a Mathematical Programming (MP) formulation for SUE and over the years, many refinements to this formulation have been proposed by researchers. SUE formulation includes an error term in the link/path travel cost function to account for the lack of perfect knowledge as well as the variation in the perception of travel cost by network users. Due to these features, SUE is considered

more appropriate for estimating network flows involving human-driven vehicles. On the other hand, DUE may be a useful and appropriate model for calculating flows of AVs in a highway network because the assumptions related to DUE (perfect knowledge and homogeneity in the perception of travel cost) may hold true in the case of AVs where the human element is largely eliminated. However, neither DUE nor SUE alone can be a suitable algorithm to estimate equilibrium flows in a network with mixed traffic of AVs and non-AVs.

There have been efforts to combine DUE and SUE approaches in past, however, they do not capture the improvement in capacities of links to accommodate a higher number of vehicles due to more efficient operations of AVs than NAVs. Harker (1988) asserted the possibility of travelers choosing routes according to behavior in either a cooperative (system equilibrium) or a non-cooperative (user equilibrium) manner. Yang (1998) proposed an advanced traveller information system (ATIS) which aims to provide traffic information to drivers in an attempt to reduce the stochasticity in computing optimal routes, at any level of market penetration, for the mixed equilibrium problem. Lo and Szeto (2002) provide a methodology outlining the trade-offs among conflicting objectives of the users, service providers, and the traffic management agency. Market penetration was modelled in an elastic manner to aid the study. Chen et al. (2017) advocate planning of the road network by allocating dedicated zones for AVs and propose a mixed-integer bi-level programming model to optimize deploying of these zones. Chen et al. (2017) analyze the technical and social challenges in the integration of AVs into shared public roads by investigating the impact of one of the first placements of AV passenger transport on public roadways. Bagloee et al. (2017) propose a model in the form of a nonlinear complementarity problem, that aims to address routing behavior of connected vehicles (CVs) which follow the SO principles, while the other vehicles pursue UE. Zhang and Nie (2018) propose a bi-level program, where the upper level determines the desired ratio between user equilibrium(UE) and system optimal (SO) users for each origin-destination(OD) pair. Despite numerous works in this domain, no study has addressed the above-stated problem: when and where dedicating links for AVs are beneficial under the mixed traffic considering the likely difference in route choice process of AVs and NAVs and platooning benefits. This study aims to bridge this gap in the literature.

Methodological framework

This study proposes a bi-level framework to determine the optimal location of dedicated links in a road network. The proposed bi-level model integrates the two methodological dimensions namely, macroscopic analysis of network flows and system level optimization strategy. These two components inform each other in a feedback loop to decide the subset of links in the network that should be dedicated for AVs at a given market penetration level for system-level benefits. Figure 1 presents a summary of the research framework for the proposed study. The multiple levels of market penetration are analyzed through scenario analysis using the bi-level framework consisting of two models (the macroscopic mixed equilibrium model and the optimization model). The output of the analysis informs at which market penetration (termed critical market penetration in this study) the first set of dedicated lanes becomes viable from the

system optimal perspective. In addition, the proposed research framework also output the set of potential links that need to be demarcated for AVs only at higher levels than the critical AV market penetration. Additionally, this research will be able to assign the appropriate sequence for including dedicated lanes in the network with increasing penetration of AVs at different parts of the city.

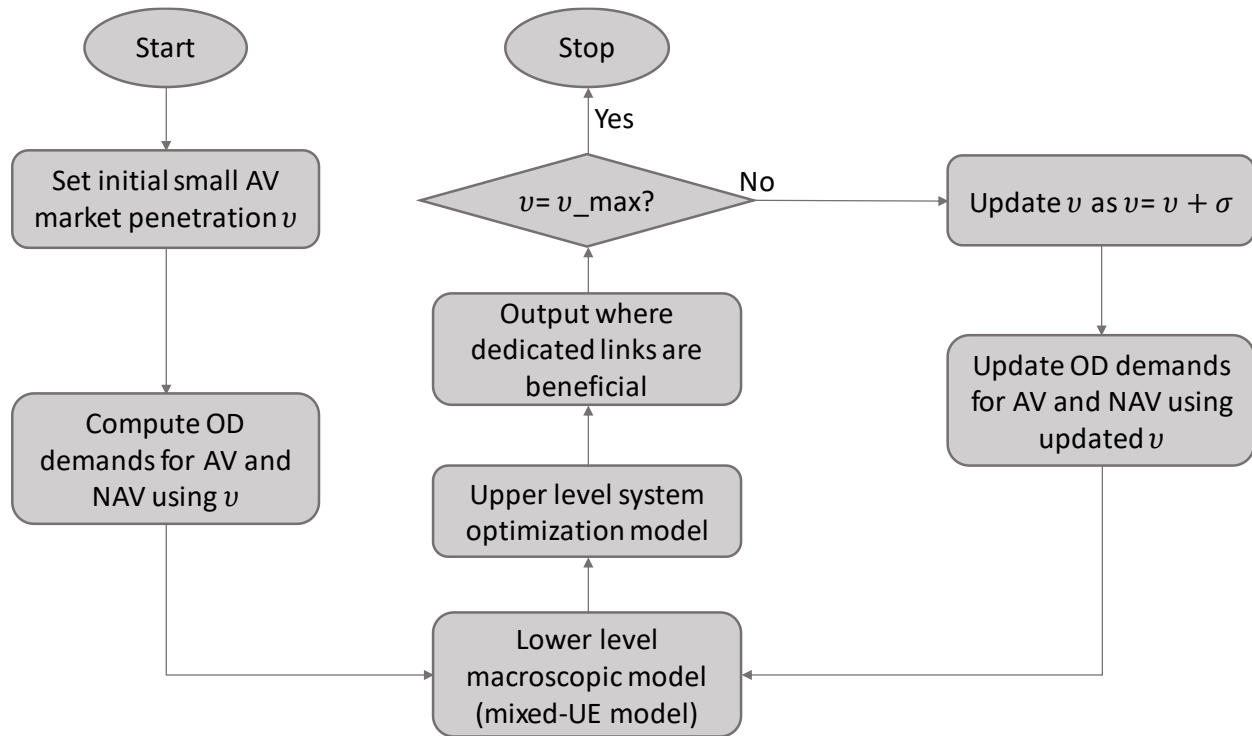


Figure 1: Bi-level Framework for the Determination of Dedicated Links

Algorithm Development

This section presents a brief description of the two models, namely lower level mixed equilibrium traffic assignment, particularly going over the flow updating process, computation of link travel times, and the optimization model for deciding the subset of links for system optimal conditions under relevant constraints. The implementation details are also systematically detailed in the next section.

Lower Level: The Mixed Equilibrium Traffic Assignment Model

The Mixed Equilibrium model is capable of estimating network flows under mixed traffic conditions of AVs and NAVs. The model incorporates the benefits of AVs, randomness among the drivers of NAVs and lane-use restrictions. It uses two different traffic assignment methods to adapt to both AV and NAV path selection processes.

The model is developed by viewing the flow equilibrium of AVs and NAVs independently, using two hypothetical representations of the real networks. These hypothetical networks are assumed to accommodate equilibrated traffic of only one type of vehicle implying the equilibrated traffic flow is computed considering the presence of only one of the vehicle types on the network at a time. This hypothetical bi-layer network equilibrium is solved in an iterative manner. The interactions among the two vehicle types from a real-world perspective is captured through link cost functions. Each iteration involves computing flows for NAVs on the hypothetical NAV network, after which the link travel times AV network is updated, which are then used by the AV flow equilibration mechanism to assign the AVs on this network. Then in the next iteration, link travel times of NAV network is updated and the NAV flows are updated on NAV network. This process is continued till convergence criteria are simultaneously met for both network layers.

The traffic assignment methods for two hypothetical networks differ in the computation of user equilibrium (UE). Wardop's First Principle, which states that "The journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route" (13), forms the basis for Deterministic User Equilibrium (DUE), which is used for computing route assignment for AVs. Such methods have deterministic characteristics and assume that drivers of AVs are machines that possess full and complete knowledge of the network and the flows in the network and select route in a rational manner. Whereas the class of Stochastic User Equilibrium (SUE) models consider the differences in driver perceptions and provide flexibility to choose paths according to their various perceptions of the network. This method of computation forms the basis of updating the NAV network flows, and these two models for AVs and NAVs interact with each other through link performance functions (cost functions) to form the Mixed Equilibrium model.

Upper Level: Optimization Model

The upper-level problem is to decide which links in the given network should be dedicated for AVs use only at a given market penetration of AVs.

A network optimization model is formulated based on insights from the literature in the domain of network design with a view to determining the optimal location of dedicated AV lanes for a given mixed vehicular demand (consisting of AV and NAV) scenario. A mixed demand scenario is defined by a myriad of unique fractions of AVs in the flows between various OD pairs. The AV market penetration level (ν), the fraction of AV versus total vehicles in the network is considered exogenous variable for this study. The optimization model seeks to maximize the network level benefits total system travel time. The decision variables for the optimization problem is a vector of binary variables. An element of this vector will be equal to 1 if the optimization model suggests that a link is warranted as a dedicated link for AVs, and equal to 0 otherwise. The cardinality of this decision variable vector is the same as the cardinality of the set of links in the network, implying that every link in the network is a possible candidate for having a dedicated AV lane.

Problem Formulation and Notation

Let the transportation network of interest be represented by a strongly connected directed graph $G(N, A)$, consisting of set of nodes N and set of links A . K^w is the set of used paths connecting an O-D pair $w \in W$, where, W is the set of OD pairs of the given network. K is the set of all used paths. Let m denotes the vehicle type where $m \in M$ and $M \equiv \{ne, e\}$ where, ne represents human-driven (hereafter referred to as NAV) and e represents AV. $f_k^{w,m}$ is the flow of vehicle type m on path k between an OD pair w and f^m is the corresponding path flow vector. $d^w > 0$ is the travel demand for the OD pair w and d is the travel demand vector. d_w^m is the travel demand for the OD pair w for vehicle type m and d^m is the corresponding travel demand vector. Flow on link a is represented by x_a . x_a^m and x^m are the link flows and vector of link flows for vehicle type m . x is the combined flow vector obtained as $x = \{x^{ne}, x^e\}^T$. The travel time of link a for vehicle type m is t_a^m and t^m is the vector of link travel times for vehicle type m . Let $\Delta = [\delta_{ak}]$ be the link-path incidence matrix, where, δ_{ak} equals 1 if path k uses link a and 0 otherwise. Let v represents the market penetration of automated vehicles.

Suppose that with each vehicle class m (AV and NAV) one associates an individual copy of the network $G^m(N^m, A^m)$ and assume that all vehicles belonging to a class use the network associated with that class only. This means that we have an extended network of double the original size of the network where each directed link has its counterpart one of which is used by AVs and another by NAVs. In addition, the travel time (cost) on a link does not depend on the flow of that link only but the flow on its counterpart link as well.

The link travel time for AV is computed as follows:

$$t_a^e = t_a^0 \left[1 + \alpha_a \left(\frac{\tilde{x}_a}{cap_a^{ne}} \right)^{\tau\beta_a} \right]$$

and the link travel time for NAV is computed as follows:

$$t_a^{ne} = t_a^0 \left[1 + \alpha_a \left(\frac{\tilde{x}_a}{cap_a^{ne}} \right)^{\beta_a} \right] + H$$

where t_a^0 and α_a, β_a, c_a are the parameters of link cost function specific to link a . t_a^0 represents the free flow travel time, and cap_a^{ne} represents the link capacity for vehicle type ne (NAV) vehicles. H and τ are paramters, whose value varies depending on whether the link is a dedicated link for AV or not. \tilde{x}_a (where $a = i, j$) represents the NAV equivalent volume which is a function of NAV volume on link $j \in A^{ne}$ as well as AV volume on its counterpart link $i \in A^e$ given as follows:

$$\tilde{x}_i = \tilde{x}_j = x_j^{ne} + cce_i(x_i^e)$$

The reduction factor, cce_i , for converting the volume of AV's into NAV equivalent volume is given as below:

$$cce_i(frac_i) = \gamma_i + (1 - \gamma_i) \exp(-\psi_i frac_i), i \in A^e$$

where γ_a and ψ_a are the parameters of link a for converting the flow of automated vehicles into non-automated vehicles equivalent.

The $frac_i$ is defined as the ratio of the volume of AVs on a link i and the sum of volumes of AVs and NAVs on a link and its counterpart, and is given as:

$$frac_i = (x_i^e)/(x_i^e + x_j^{ne}), \forall a \in A$$

The path flow distribution on the two hypothetical networks (for AV and NAV) depends on the underlying assumption that AVs have full information on the network and they follow deterministic user equilibrium (DUE) while NAVs follow the stochastic user equilibrium (SUE). The mixed user equilibrium flows of AVs and NAV is determined using bi-layer framework where flows in two layers are moved towards SUE and DUE sequentially with the feedback through link cost functions starting from all-or-nothing (AON) assignment as shown in Figure 2.

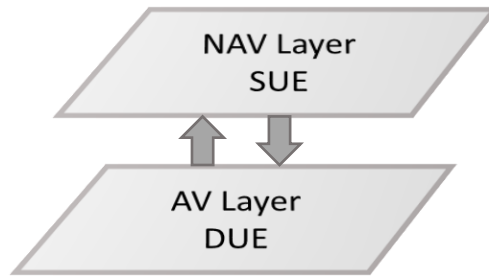


Figure 2: Bi-layer Framework for the Determination of Mixed User Equilibrium

The AV path flow update is carried out using the SPSA algorithm developed by Kumar and Peeta (Kumar and Peeta, 2014). The details of the SPSA algorithm is not presented here for brevity. The NAV ($m=ne$) path flow update as per the stochastic user equilibrium is carried using the logit model (using following two equations):

$$p_k^{w,ne} = \frac{\exp(-\theta c_k^{w,ne})}{\sum_{k \in K^w} \exp(-\theta c_k^{w,ne})}, \quad \forall k \in K^w, w \in W$$

$$f_k^{w,ne} = p_k^{w,ne} d_w^{ne}, \quad \forall k \in K^w, w \in W$$

where, θ is a positive real valued parameter related to variation in perception of path travel times, and 'exp' represents the exponential function.

The upper-level optimization model is represented as follows:

$$\min Z(\phi) = \sum_{i \in A} x_i^e(\phi) t_i^e(x) + x_i^{ne}(\phi) t_i^{ne}(x)$$

Subject to:

$$\phi_a \in \{0,1\}, \forall a \in A^e$$

Where ϕ is the vector of binary variables ϕ_a . The cardinality of vector ϕ is $|A|$ and its element ϕ_a represents whether a link a of original network $G(N, A)$ is dedicated ($\phi_a = 1$) or not ($\phi_a = 0$).

Implementation Details

The flow logic of the Mixed Equilibrium model can be understood by the flow diagram illustrated in Figure 3. The algorithm begins with All-or-Nothing (AON) assignment. The AON assignment is simultaneously carried out for AV and NAV vehicle layers and involves computing the shortest path for each O-D pair and assigning the OD demand (according to the AV market penetration value) to those paths for respective hypothetical network layers. The link flows and link costs are updated for each vehicle type after the AON. Next, we initiate the mixed-equilibrium flow update logic, checking the convergence criteria after each network update (except after AON). The algorithm executes sequentially path set update and path flow update, first for NAV vehicle types, followed by AV. One iteration is completed after NAV and AV flows get updated. Once an iteration is completed, the convergence test is carried out. The algorithm is terminated on satisfying this test, else commences with the next iteration. The convergence criteria for automated vehicles is measured using the normalized gap (*Ngap*) or average excess cost, given by the following equation:

$$Ngap = \frac{\sum_w \sum_k c_k^{w,e} f_k^{w,e} - \sum_w \sum_k c_{min}^{w,e} f_{min}^{w,e}}{\sum_w \sum_k f_k^{w,e}}$$

The convergence criteria for NAV vehicles is logit move gap (*Lgap*) between two consecutive iterations given as follows:

$$Lgap = \frac{\sum_w (\sum_k |p_{k,iter}^{w,ne} - p_{k,iter-1}^{w,ne}|) d_w^{ne}}{\sum_w d_w^{ne}}$$

The step size is another important parameter that merits mention from an implementation perspective. The SPSA algorithm uses step size λ for updating path flows for the AV vehicle type. SPSA uses the line search to find the step size (for details see (Kumar and Peeta, 2014)), however, for computational simplicity, it is obtained using the following expression in this study:

$$\lambda_{w,iter} = (iter^{-(2/3)} \lambda_{max}^w) / 10$$

where $iter$ is the iteration number and λ_{max}^w is the maximum permissible step size for OD pair w , calculated as per the SPSA algorithm (Kumar and Peeta, 2014) as follows:

$$\lambda_{max}^w = \frac{1}{\max(c_k^{w,e} - c_{min}^{w,e})}$$

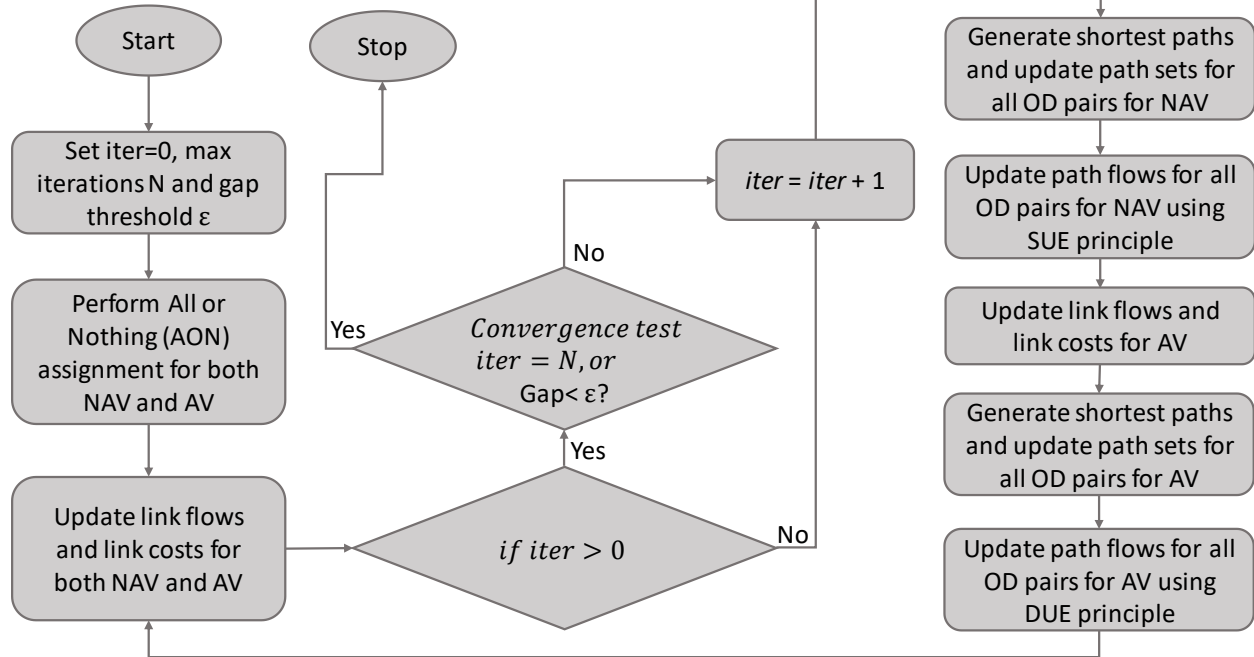


Figure 3: Implementation Details for the Lower Level MUE Traffic Assignment

Numerical Experiments

We consider a small test network for conducting our experiments. This facilitates to conduct a numerical experiment for many scenarios and analyze the numerical results. The model is applied to a network consisting of 15 nodes and 21 links (see Figure 4). The number inside the node represents the node number and number above the link represents the link number. There are three origin nodes labeled 1, 2 and 3 and three destination nodes labeled as 12, 13 and 14.

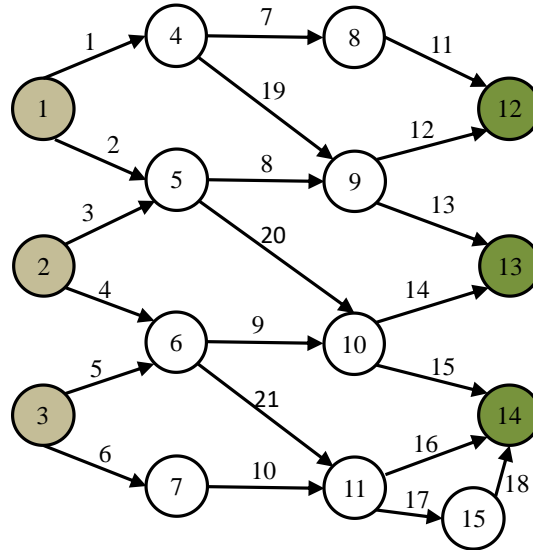


Figure 4: Test Network

Upper-level problem was solved using binary particle swarm optimization and was coded in MATLAB and lower-level problem was coded in c++. The optimal dedicated links were determined using the methodology proposed in this paper for 40 scenarios. These scenarios correspond to market penetration of AVs starting from 1% to 40% with an increment of 1%. The total system times (TSTT) for the network for two cases namely without dedicated links and with optimal dedicated links were compared and is shown in Figure 5. The numerical results indicate that TSTT reduces with increasing market penetration for both cases. In addition, the TSTT under optimal dedicated links are smaller than the case when there are no dedicated lanes for each scenario. The difference in the system time between two cases for all 40 scenarios are plotted in Figure 6. It is observed that the market penetration of 1% results in the maximum reduction of the system travel time and the difference between the TSST of two cases (savings in TSTT due to dedicating links for AVs) decreases with increasing market penetration.

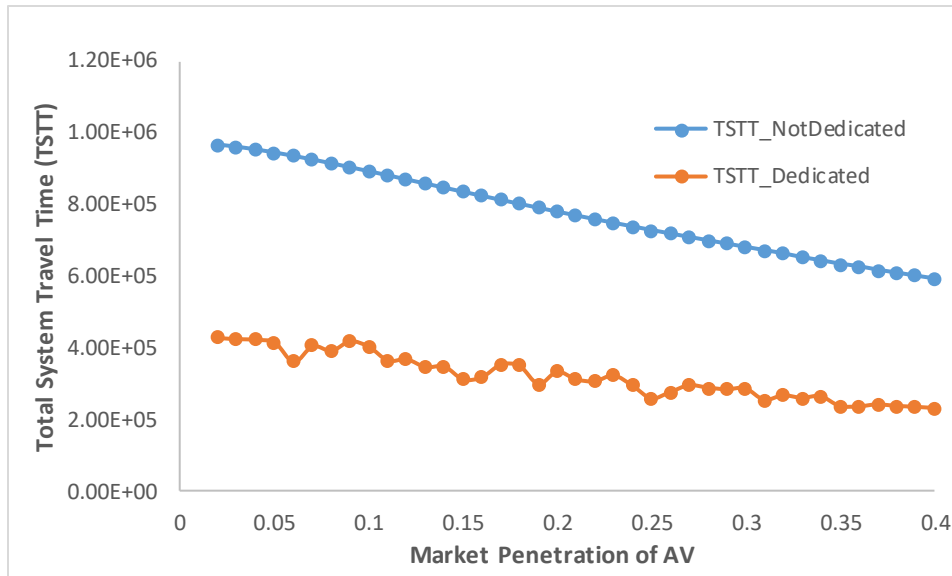


Figure 5: TSTT With and Without Dedicated Lanes

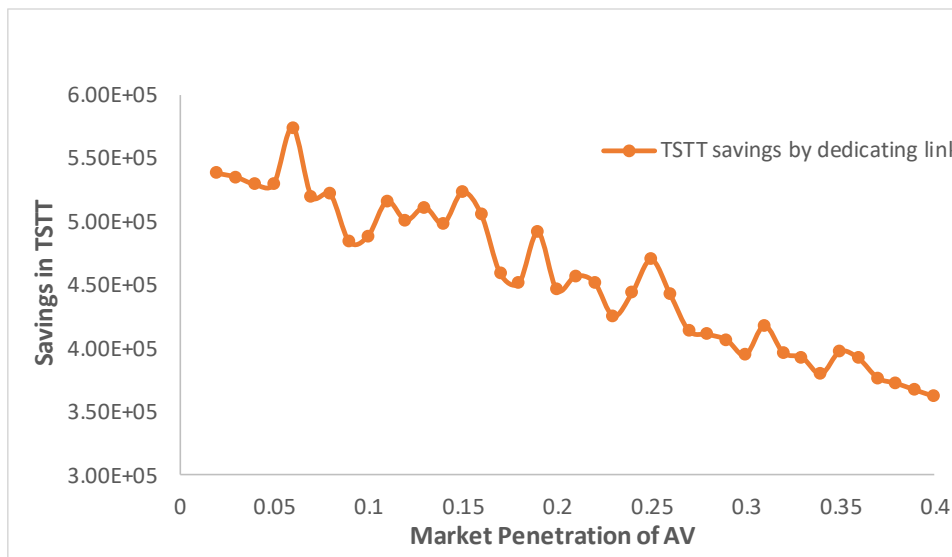


Figure 6: TSTT Savings Achieved by Optimal Dedicated Lanes

Table 1. Dedicated AV Links at Various Market Penetrations

v	Link 1	Link 2	Link 3	Link 4	Link 5	Link 6	Link 7	Link 8	Link 9	Link 10	Link 11	Link 12	Link 13	Link 14	Link 15	Link 16	Link 17	Link 18	Link 19	Link 20	Link 21
0.01	1	1	1	1	0	1	1	1	0	1	1	1	0	0	1	1	1	0	0	1	0
0.02	1	1	0	1	0	0	1	1	1	0	0	0	0	1	1	0	1	1	1	0	0
0.03	0	0	1	1	0	1	0	0	0	1	1	1	1	0	0	0	1	0	0	1	0
0.04	1	1	1	1	0	1	0	1	1	1	1	0	1	1	0	0	1	0	1	1	1
0.05	1	1	0	1	0	0	0	1	0	0	1	0	0	1	1	0	0	1	1	0	0
0.06	1	1	1	1	0	0	1	0	0	1	0	1	0	0	1	0	0	1	1	1	1
0.07	1	1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
0.08	1	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0
0.09	1	0	0	0	0	0	0	1	1	1	0	0	1	1	1	0	1	1	1	0	1
0.1	1	1	0	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	0	1	1
0.11	1	0	1	1	0	1	0	1	1	0	1	1	0	0	0	0	1	0	0	1	0
0.12	1	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0
0.13	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	1	1	0
0.14	1	1	1	0	1	1	0	0	0	1	1	1	1	1	1	0	1	0	1	0	0
0.15	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0	1	0	0	0	0	0
0.16	1	1	1	1	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	0
0.17	0	0	0	1	0	0	1	0	0	0	1	1	0	1	1	1	1	0	1	1	0
0.18	1	0	0	1	0	0	0	1	0	0	0	0	0	0	1	1	1	1	1	1	0
0.19	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	0	0	1	1	1	0
0.2	1	0	0	1	1	0	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0
0.21	1	1	1	0	1	0	0	1	0	1	1	0	1	1	1	0	1	0	1	1	1
0.22	1	1	1	1	1	0	0	1	0	1	1	0	1	1	1	0	1	0	1	1	1
0.23	0	0	0	1	1	1	1	1	0	1	1	1	1	0	1	0	0	1	0	1	1
0.24	1	1	1	1	1	1	1	0	0	1	0	0	0	1	1	0	0	0	0	0	0
0.25	1	0	1	1	1	1	0	1	1	1	0	0	0	1	1	0	1	0	1	0	0
0.26	0	0	1	1	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0
0.27	1	1	0	1	1	1	1	1	0	0	1	1	1	0	0	1	1	1	1	0	0
0.28	1	1	1	1	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	0
0.29	1	0	1	1	1	0	0	0	1	1	0	1	1	0	0	0	1	0	0	0	1
0.3	0	0	1	1	1	1	0	0	0	1	1	0	0	1	1	0	1	0	1	0	1
0.31	1	1	1	1	1	1	0	0	0	1	0	0	0	1	1	0	0	1	1	1	1
0.32	1	1	1	1	0	0	0	0	0	1	1	0	1	1	1	0	1	0	1	1	0
0.33	1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
0.34	1	1	0	1	0	0	1	0	0	1	0	0	0	0	0	0	1	1	1	0	0
0.35	1	1	1	1	1	0	0	0	0	1	1	0	1	1	1	0	0	0	1	1	0
0.36	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1	0	1	1	0
0.37	1	1	0	1	1	0	0	0	0	1	1	0	1	0	0	0	0	1	1	1	0
0.38	1	1	1	1	1	1	0	0	0	0	1	0	0	1	1	0	1	1	1	0	0
0.39	1	1	0	1	1	0	0	0	0	1	1	0	1	0	0	0	1	1	1	1	0
0.4	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	1

Table 1 presents the summary output of numerical experiments of all scenarios. It shows which links need to be dedicated at various market penetration (v) for minimizing the total system travel time. A value of 1 indicates the link is dedicated (also shaded in table) and 0 indicated link is not dedicated. The results indicate that the number of links dedicated to AV is not a monotonic and increasing function of v . However, there are some links that are dedicated under a higher number of scenarios than other links and will be a probable candidate for investments.

Conclusions

Automated vehicle (AV) technology is advancing at a rapid pace. AV holds the promise to solve both congestion problem along with the safety issues particularly arising due to human error. Although technical and legal aspects of the AV have been dealt with by multiple studies, the infrastructure readiness for realizing the benefits of AV has received little attention. This study aims to bridge this gap. In particular, the study focus is where and when to have dedicated links for system-level benefits. This knowledge can also help in more focused investment decisions for making infrastructure ready for AV technology. The study presents a bi-level formulation for solving this problem. The upper level aims to achieve system optimal goals and lower level captures the network user response. The lower-level is solved as mixed equilibrium problem, where, NAVs are assigned as per SUE and AVs are assigned as DUE. The numerical experiments are carried out to test the validity of the proposed framework. The results of the numerical experiment indicate that dedicated lanes can lead to network flows that can yield significant savings in total system travel time.

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