DEDICATED LANES FOR CONNECTED AND AUTOMATED VEHICLES ON FREEWAYS: A SIMULATION STUDY

by

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ABSTRACT

Connected and Automated Vehicles (CAVs) may have the capability to relieve congestion by improving roadway capacity by enabling vehicles to safely follow each other with smaller headways than traditional vehicles. Several studies suggest this effect will be maximized when CAVs are able to platoon – or group together in long caravans without interruption from traditional vehicles. One way to stimulate platooning is to introduce dedicated lanes for CAVs. However, paving additional lanes would be expensive and preventing traditional vehicles from using one of the existing lanes would be detrimental to capacity when CAV market penetration rates are low. Policymakers and traffic engineers would benefit from knowing when dedicating a CAV lane would increase overall roadway performance. As such, this study aims to provide a basis for determining when the implementation of a Dedicated CAV Lane (DCAVL) would be beneficial to typical three-lane freeways. Total vehicle delay was used as the performance metric for assessing when it is ideal to have a DCAVL. Factors that can influence this decision – such as Market Penetration Rate (MPR) of CAVs, CAV-CAV headway, and demand volume – were considered for analysis. PTV Vissim was utilized to develop a microsimulation model for this analysis. 198 scenarios were created, each reflecting a unique combination of the input parameters. A base scenario with no DCAVL was used to serve as a basis for comparison. A scenario comparison analysis was utilized to ultimately determine when a DCAVL will cause total vehicle delay to improve beyond the base scenario. The results of this study indicate that a three-lane freeway with a DCAVL will consistently begin to outperform the same three-lane freeway without a DCAVL when the MPR is between 34% and 37%. This trend is impacted very

minimally by the CAV-CAV headway and the demand volume of the scenario. While these results are subject to various limitations, they suggest that the successful implementation of a DCAVL may only be affected by the MPR of the scenario and that this MPR may fall within a very small range. As such, this research effectively provides a macroscopic view of the effects CAVs and DCAVLs will have on roadway performance and serves as a foundation for policymakers, traffic engineers, and researchers to base their future work upon.

DEDICATION

To my incredible mother, for her limitless love and support.

ACKNOWLEDGEMENTS

I am honored to have the opportunity to thank the countless advisors, professors, colleagues, friends, and family members whose support has ultimately enabled my pursuit of higher education and this research agenda. Without these special people in my life, I would not have been capable of producing the work presented in this paper. For this, I am forever grateful.

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I. INTRODUCTION

Between the years of 1980 and 2016, vehicle miles traveled in the United States grew over 2.0% per year while total lane miles only grew by about 0.3% per year (Federal Highway Administration (FHWA), 2017). Growth in vehicle miles traveled, while expected to slow, is forecasted to be between 0.7% and 1.0% between years 2017 and 2047 (Federal Highway Administration (FHWA), 2019), continuing to outpace total lane mile growth. This inability of our roads to meet traffic demand has led to significant congestion that will continue to worsen; it is evident we must use our infrastructure more efficiently to resolve this growing issue.

One way to maximize roadway efficiency is to utilize new technologies and take advantage of the assets they provide. Connected and Automated Vehicles (CAVs), in particular, offer promising benefits to roadway efficiency, especially at Level 5 autonomy. CAVs are expected to relieve congestion by improving roadway capacity through reducing time headways between consecutive vehicles. This effect is expected to maximize when CAVs are able to platoon – or group together in long caravans without interruption from traditional vehicles (Ghiasi, Hussain, Qian, & Li, 2017). Unfortunately, on today's roads, it is unlikely that CAVs will be able to platoon effectively and thus their impacts will be diminished, especially at low Market Penetration Rates (MPRs) (Pinjari, 2014).

One way to address these issues and stimulate platooning is to reserve one or more of the existing lanes solely for CAVs, known as a Dedicated CAV Lane (DCAVL). This would be a cost-effective approach as no new lanes would need to be constructed. However, reserving lanes for CAVs will be detrimental to overall capacity when they are underutilized, i.e. when the MPR of CAVs is low. Policymakers, future researchers, and traffic engineers would benefit from knowing when the conversion of a normal lane to a DCAVL would improve overall roadway performance. As such, this study aims to provide a basis for determining when the implementation of a DCAVL would be beneficial to overall roadway capacity by conducting a macroscopic scenario analysis of a typical freeway segment utilizing PTV Vissim.

The key performance metric used to analyze roadway capacity is total vehicle delay. When the average total vehicle delay of a given scenario surpasses the control scenario with no DCAVL, it would be beneficial to implement the DCAVL at that point. In the realm of CAVs, there are countless factors that can influence this performance metric, the majority of which may not even be known at this point in the technology's infancy. Thus, they are impractical to evaluate with the data we have today. This is the primary motivation for this research. By conducting a macroscopic scenario analysis based on several known key input parameters, this study is able to provide a guideline for the implementation of DCAVLs today that policymakers and traffic engineers can begin to base their future deployment strategies upon.

In this study, the primary factors considered are the MPR of CAVs, demand volume, and CAV headways. The first two are simple independent variables used as inputs. The third, CAV headways, cannot be anticipated exactly; however, it can still be used as an independent variable because experts largely agree on the range they will fall within (Ghiasi, 2018). Thus, each of these three factors will be independent input variables in this analysis.

Another important set of variables is the number of normal vehicle lanes and the number of DCAVLs. In the future, there could be multiple DCAVLs on a freeway with any number of traditional lanes. However, due to the infancy of this research area, this study will focus on a very basic lane scenario where a typical 3-lane freeway is managed with 1 lane reserved as a DCAVL and the remaining 2 lanes serving as traditional traffic lanes.

The combination of these variables creates several distinct scenarios. By varying the MPR, the demand volume, and the CAV headway over a standard range, a wide array of potential scenarios that could realistically exist in the future of our transportation network will be analyzed. Ultimately, 198 unique scenarios will be created and analyzed in this endeavor. Each scenario will be run in Vissim five times, thus creating data from 990 separate simulations to be analyzed in this study.

PTV Vissim version 11.00-03 is utilized to construct the basic network, create each scenario, run the simulations, and ultimately generate the total vehicle delay data used for the analysis.

II. LITERATURE REVIEW

In the last few years, CAVs have drawn significant attention from policymakers, engineers, and researchers in the transportation industry. Despite the infancy of the technology, they have been widely researched, with topics ranging from their potential impact on capacity, accessibility, safety, and traffic revenue.

Many assert that CAVs can provide numerous socioeconomic benefits to society. In regard to accessibility, a study conducted by the Society of Motor Manufacturers and Traders (SMMT) showed that over 50% of people feel their mobility is restricted – a problem CAVs could help solve – and 48% of people believe reducing driving stress is one of the greatest benefits of CAVs (Hawes, 2017). In regard to safety, the National Highway Traffic Safety Administration (NHTSA) states that 94% of serious crashes are due to human error, many of which have the potential to be avoided through CAV technologies (National Highway Traffic Safety Administration (NHTSA), 2017). It is clear CAVs should be extensively researched to explore their potential benefits.

While these are very important benefits of CAVs, many transportation engineers are interested in the impacts of CAVs on roadway capacity and thus traffic congestion. It is commonly presumed that CAVs have the ability to increase roadway capacity by minimizing reaction time and thus safe following distances. In a paper published in the Institute of Transportation Engineers (ITE) journal in 2016, D. Farmer produced an early projection that CAVs could increase roadway capacity by as much as 100%, from 2,000 vphpl to 4,000 vphpl (Farmer, 2016). This was found by reducing the approximate perception/reaction times of human drivers from 1.5 seconds to a conservative estimate of 0.1 seconds for CAVs. This same analysis also found that CAVs could increase freeway travel speeds by over 20%. However, it is important to note that these brief calculations were done using standard speed-flow-density relationships, with an integral assumption being that the fleet will eventually be 100% CAVs.

Although it is unlikely our transportation fleet will be homogeneously filled with CAVs in the near future, many agree a significant portion will exist. Bansal and Kockelman predict that the vehicle fleet will have between 24.8% and 87.2% Level 4 AV penetration by 2045 depending on the amount prices drop and the amount customers' willingness to pay increases (Bansal & Kockelman, 2017). Even more drastically, Arbib and Seba predict that by 2030, 95% of U.S. passenger miles traveled will be served by on-demand AVs – rather than individually-owned vehicles – and that this rapid shift in our transportation system will keep an additional $1 trillion in American consumers' pockets each year (Arbib & Seba, 2017).

With a large MPR of CAVs, it is clear significant impact can be made on our transportation system's performance. Ghiasi, Hussain, Qian, and Li showed that capacity can be impacted by CAV headway, platooning intensity, and MPR by developing an analytical capacity model based on a Markov chain (Ghiasi, Hussain, Qian, & Li, 2017). They then used this concept to develop a lane management model for determining the optimal number of DCAVLs given these inputs. However, they used a static approach focused on platooning and did not consider microscopic traffic dynamics in their analysis. This was a primary motivation for the utilization of microsimulation software in this study.

M. Makridis, K. Mattas, B. Ciuffo, M. Raposo, T. Toledo, and C. Thiel utilized Aimsun software to conduct a preliminary analysis of the effects of both Automated Vehicles (AVs) and CAVs on average harmonic speed, an indicator of roadway performance. Their simulations –

composed of AVs and CAVs interspersed throughout the vehicle fleet – concluded that CAVs can indeed be beneficial to the network, especially at very high MPRs (Makridis, et al., 2018). The scope of their work did not include managed lanes such as DCAVLs.

Talebpour, Mahmassani, and Elfar focused primarily on the effects of DCAVLs on congestion and travel time. Their research utilized a self-developed microsimulation framework to assess the effects of CAV MPR on the flow-density relationship of both a two-lane and four-lane highway. Most importantly, they analyzed different CAV driving behaviors where the vehicles could either operate autonomously without restrictions, could drive in any lane but could only operate autonomously in the DCAVL, or were forced to use the DCAVL. They concluded that CAVs having the ability to operate autonomously whether in the DCAVL or not provided the most impact on minimizing congestion and maximizing throughput (Talebpour, Mahmassani, & Elfar, 2017). However, they did not include varying CAV headways in their scenario analysis and used a self-developed car-following model to simulate the movement of their vehicles rather than standard microsimulation software.

Although the ability for CAVs to increase capacity is evident, many wonder if the additional demand they induce will offset this. J. Auld, V. Sokolov, and T. Stephens utilized a transportation system model called POLARIS to analyze the effect changes in capacity would have on Vehicle Miles Travelled (VMT). They concluded that an increase in capacity of 80% would cause an additional 4% induced VMT that would offset some of the benefits CAVs provide (Auld, Sokolov, & Stephens, 2016). This is arguably negligible and thus shows that the increase in capacity would be very beneficial.

Looking further into the actual deployment of these DCAVLs, Chen, He, Zhang, and Yin developed a time-dependent model that aims to introduce dedicated lanes into our transportation network throughout future years while minimizing social costs and promoting the adoption of CAVs (Chen, He, Zhang, & Yin, 2016).

Although current research has largely evaded the use of standard microsimulation software to analyze the effects of DCAVLs on roadway performance, other types of managed lanes have been researched extensively and serve as great procedural foundations for the research proposed in this study. A prime example is High Occupancy Vehicle (HOV) lanes. Weyland, Buck, Vortisch, and Zeidler utilized PTV Vissim to analyze whether the introduction of an HOV lane on a German freeway would be beneficial to roadway performance (Weyland, Buck, Vortisch, & Zeidler, 2018). G. Gomes, A. May, and R. Horowitz presented and applied a procedure for constructing a PTV Vissim model of a congested complex freeway in California that included an HOV lane and concluded that the microsimulation software was well-suited for simulating the advanced driving interactions produced by these complicated features (Gomes, May, & Horowitz, 2004).

It is evident there is a large gap in the current research where CAVs, DCAVLs, and their effects have not yet been assessed using standard microsimulation software. One potential reason for this is the fact there is very limited amounts of data on CAVs and the way they interact with other vehicles. This lack of data makes the development of a model very difficult. However, Sukennik and the CoEXist team did extensive research on this exact topic. They used field data collected from a test track in Helmond, Netherlands to develop a driving behavior model in PTV Vissim that reflects the way these vehicles operate (Sukennik, 2018). Because this project is affiliated directly with the PTV Group, it is an excellent foundation to base a CAV microsimulation model upon.

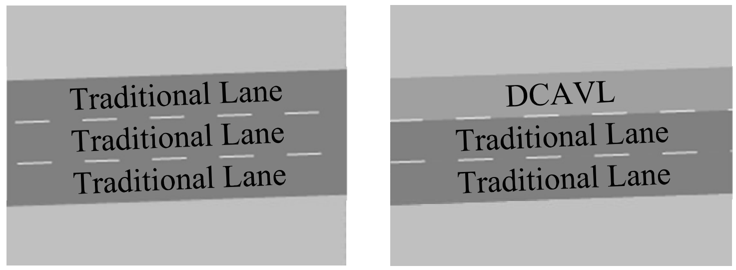
The Methodology section below introduces the variables analyzed in this study, the construction of the simulation framework, and the use of the total delay and latent delay metrics in Vissim to conduct a thorough analysis of the freeway.

III. METHODOLOGY

PTV Vissim is a very commonly used microsimulation software package for the creation and evaluation of complex roadway networks. Because the purpose of this research is to provide a broad array of future researchers and traffic engineers a foundation upon which to base their specific models, Vissim was chosen for its familiarity to a large user base. Version 11.00-03 was used for this study.

Three distinct input variables are examined in this study. These are the MPR of CAVs, the demand volume, and the CAV-CAV headway. The MPR ranges from 0-100%, increasing initially at 5% increments until 30%, then increasing at 10% increments until 50%, and finally increasing at 25% increments until 100%. This allowed the simulations to be focused on lower MPRs where the results are expected to be most insightful. The demand volumes studied are 4000, 5000, and 6000 vehicles. These values were chosen because they straddle a standard three-lane highway's capacity, which is where a DCAVL is expected to have the most impact. Lastly, the CAV-CAV headways studied were 0.5, 1.0, and 1.5 seconds. These values were established as a result of A. Ghiasi's extensive literature review on CAV headway distributions which notes most scholarly papers use CAV-CAV headways anywhere from 0.3-2.0 seconds (Ghiasi, 2018).

Because the fundamental goal of this paper is to determine when this three-lane freeway segment with one lane reserved for CAVs will outperform the same freeway segment without the DCAVL, two distinct lane scenarios were created in addition to the variables above. One served as the control *without* the DCAVL (Figure 1a); the other served as the experiment *with* the DCAVL (Figure 1b). The lighter gray lane in Figure 1b represents the DCAVL.



(a) (b)

Figure 1. Vissim Model without DCAVL (a), with DCAVL (b)

Various combinations of the three variables listed above – as well as two separate lane scenarios for the control and experiment – created numerous unique scenarios to be analyzed in this study. First, each of the 3 demand scenarios were matched with each of the 3 headway scenarios to create 9 primary models (Table 1). Within each model, the 11 MPR scenarios and the 2 lane scenarios combined to make 198 total scenarios to be tested in Vissim. Each is run in Vissim five times, thus creating data from 990 different simulations to be analyzed. These scenarios are illustrated in a tree diagram below (Figure 2).

Table 1. Nine Primary Models Analyzed

Demand Volume	CAV-CAV Headway: 0.5 sec	1.0 sec	1.5 sec
4000	4000 vehicles 0.5 seconds	4000 vehicles 1.0 seconds	4000 vehicles 1.5 seconds
5000	5000 vehicles 0.5 seconds	5000 vehicles 1.0 seconds	5000 vehicles 1.5 seconds
6000	6000 vehicles 0.5 seconds	6000 vehicles 1.0 seconds	6000 vehicles 1.5 seconds

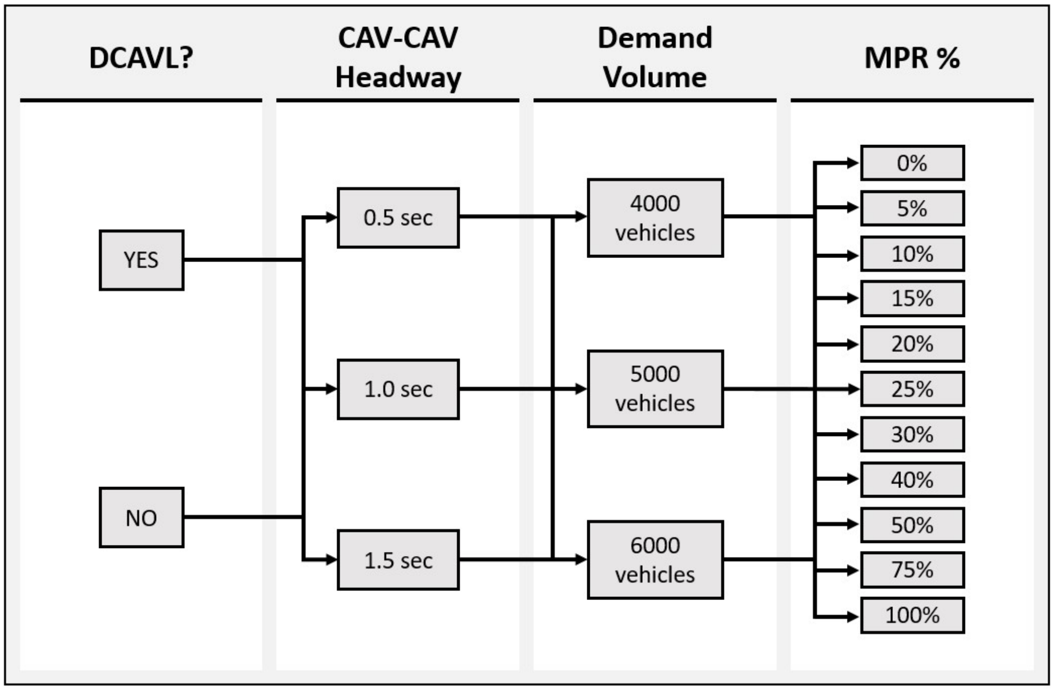


Figure 2. Summary of Scenarios

Several key assumptions were made to isolate the effects of these variables and limit unwanted noise in the data. First, to highlight the effect of the CAV driving behavior developed by the CoEXist team, CAVs were assumed to operate the same as traditional vehicles in regard to speed limits and thus both vehicle types were given the same desired speed curve. A typical freeway in Alabama has a posted speed limit of 70 mph, so the desired speed curve ranged between 65 mph and 90 mph (Figure 3). This curve was modeled very closely to a default desired speed curve within Vissim.

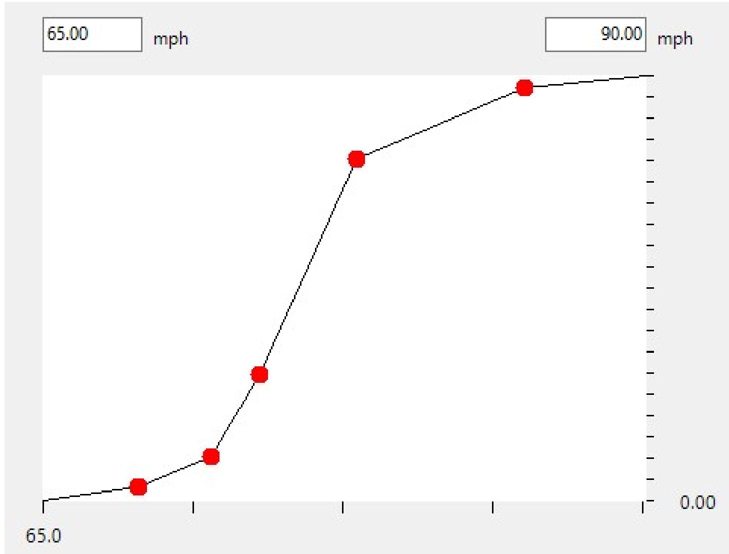


Figure 3. Desired Speed Curve

Second, CAVs were assumed to follow traditional vehicles with the same headway that traditional vehicles would follow each other with. This was done to maximize the efficiency of CAVs in platoons and thus maximize the effectiveness of the DCAVL. It is understood that many researchers assume CAVs following traditional vehicles will likely require shorter headways than traditional vehicles following each other (Ghiasi, Hussain, Qian, & Li, 2017), but with the scope of this research in mind, this assumption was made to minimize complexity.

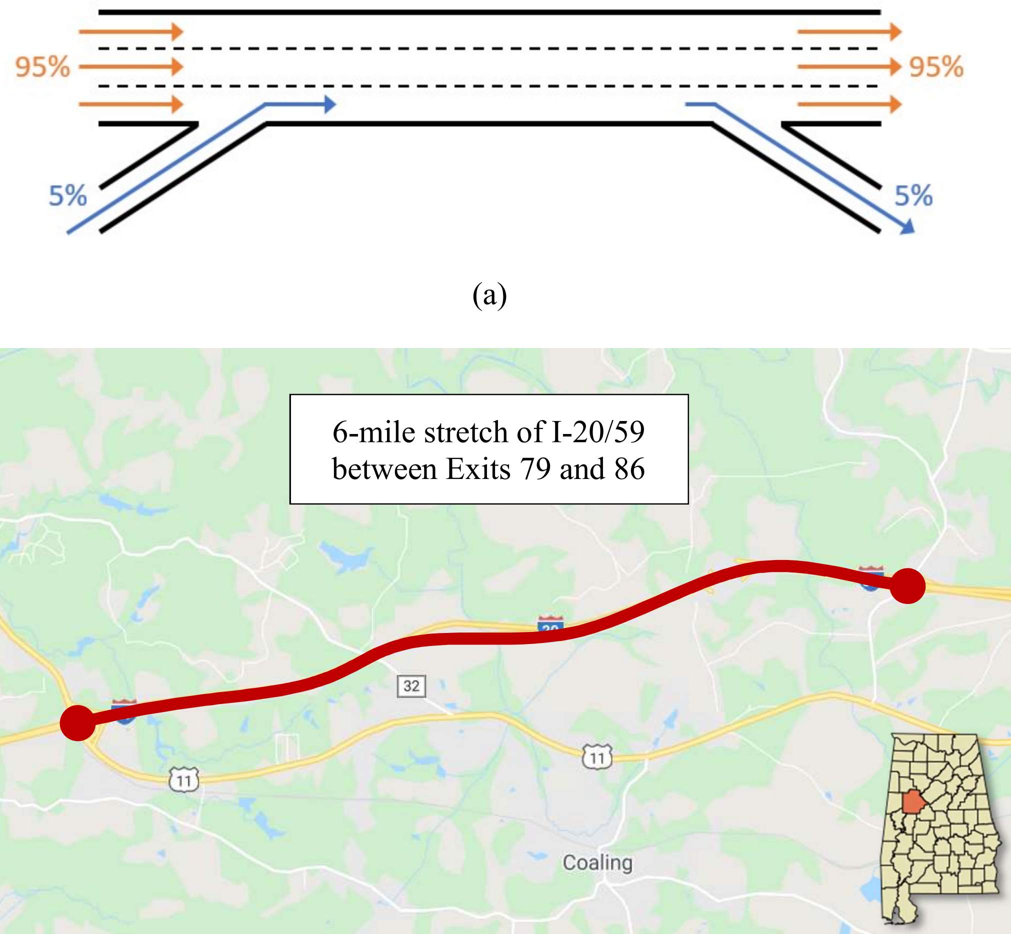
Lastly, for simplicity, it was assumed that traditional vehicles would follow other traditional vehicles at a minimum headway of 2.0 seconds. To be consistent with the above assumption, a CAV following a traditional vehicle and vice-versa would also have a minimum headway of 2.0 seconds (Table 2).

Table 2. Headway Distribution based on Following Scenario

Car Following Scenario	Headway
CAV following another CAV	0.5, 1.0, 1.5 seconds
CAV following a Traditional Vehicle	2.0 seconds
Traditional Vehicle following a CAV	2.0 seconds
Traditional Vehicle following another Traditional Vehicle	2.0 seconds

Every value in Vissim other than the ones noted in these assumptions and the input variables was left as the default. For example, all the values in both the CAV and traditional vehicle driving behaviors were left as the default other than the headway time distribution. This was done to uphold the purpose of this paper – to retain familiarity to as many Vissim users as possible. In a typical microsimulation for specific planning purposes, a traffic engineer would alter many of these values in an attempt to calibrate their model with real world data collected from their site. However, this research is not typical, and there is extremely limited data on CAVs today with absolutely none on any road with specific conditions such as MPRs, demands, or headways. For these reasons, calibration to real data is not possible, so many default values were kept in an attempt to remain consistent and familiar to a broad audience.

Construction of the simulation framework first involved choosing a site for the model to be based upon. To maintain the goal of limiting noise and providing a fundamental assessment of DCAVL performance, a very simple, basic site was needed. Specifically, a long, familiar three-lane freeway segment was desired to assess the effects of the DCAVL over several miles. Only one entrance ramp and one exit ramp at the beginning and end of the site, respectively, was ideal. These ramps were assumed to comprise about 5% of the freeway's total demand volume; the remaining 95% would exist as vehicles already on the freeway (Figure 4a). This would encourage some weaving throughout the simulation without overcomplicating the site. Additional access points were not desired in an effort to focus the results on the DCAVL's impact over a long, isolated freeway stretch. Minimal geometric features were also desired to limit variability caused by features such as sharp turns. These characteristics were crucial for maintaining the goal of primarily assessing the effects of the dedicated lane on the freeway's performance. As such, the 6-mile freeway stretch of I-20/59 near Coaling, Alabama between exits 79 and 86 was chosen (Figure 4b).



(b)

Figure 4. Desired Site Concept (a), Actual Site Used (b)

Once the site was built and each scenario was constructed in Vissim, the simulations were run and data points were recorded. The key performance metric used in this study was total vehicle delay. This metric accounted for all the delay the vehicles experienced going through the simulation as well as the vehicles that were not able to begin the simulation due to congestion. As such, it produces more accurate and consistent results than a metric like average vehicle travel time, which can only be recorded for the vehicles that successfully complete the simulation. Because the purpose of a DCAVL is to improve congestion, a metric that can be utilized around the freeway's capacity point was crucial. In Vissim, the total vehicle delay of all cars in the network is split into two separate results: total delay and latent delay. Total delay is the sum of all the delay of the active or completed vehicles; latent delay is the sum of all the delay of the vehicles that have not started the simulation yet. By adding both of these metrics together, the delay experienced by the entire demand volume is accounted for with a single metric termed in this paper as "total vehicle delay". The results from these simulations are compiled in the section below.

IV. RESULTS

Each of the 198 scenarios briefed in the Methodology section were run 5 times in Vissim to generate data from 990 total simulations. The total delay (active/past) and latent delay (future) of the entire network were the primary metrics used for the analysis in this Results section and the forthcoming Discussion section. For each scenario, the averages of the total delay and latent delay were added together, creating a total vehicle delay metric that accounts for the delay felt by the entirety of the demand volume: vehicles that successfully completed the simulation, vehicles still in the process of completing the simulation, and vehicles that were unable to begin the simulation due to overcongestion. The results of this total vehicle delay metric are shown below.

The first group of figures shows the data collected from the three models with a demand volume of 4000 vehicles (Figures 5-7). In each of these – regardless of CAV-CAV headway – the total vehicle delay of the freeway *with* the DCAVL (experiment) begins at 0% MPR with 1153 hours, while the total vehicle delay of the freeway *without* the DCAVL (control) begins at 0% MPR with 408 hours. The CAV-CAV headway is irrelevant at this point because there are no CAVs in the model. The experiment is expected to always drastically underperform at this point.

In the model with a 0.5 second CAV-CAV headway, the experiment begins to outperform the control at about 37% MPR with about 230 hours of total vehicle delay, represented by the gray dotted line (Figure 5). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 7 hours of total vehicle delay. In every model, the two lane scenarios are expected to always meet again at this point because the DCAVL will be irrelevant at 100% MPR. The maximum benefit of the

DCAVL seems to occur at about 43% MPR, where the total vehicle delay of the experiment is about 30 hours less than the control, indicated in the graphs by the solid green line labeled “Net”.

In the model with a 1.0 second CAV-CAV headway, the experiment begins to outperform the control at about 35% MPR with about 280 hours of total vehicle delay (Figure 6). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 12 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 43% MPR, where the gap in the total vehicle delay is about 80 hours.

In the model with a 1.5 second CAV-CAV headway, the experiment begins to outperform the control at about 34% MPR with about 330 hours of total vehicle delay (Figure 7). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 22 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 42% MPR, where the gap in the total vehicle delay is about 105 hours.

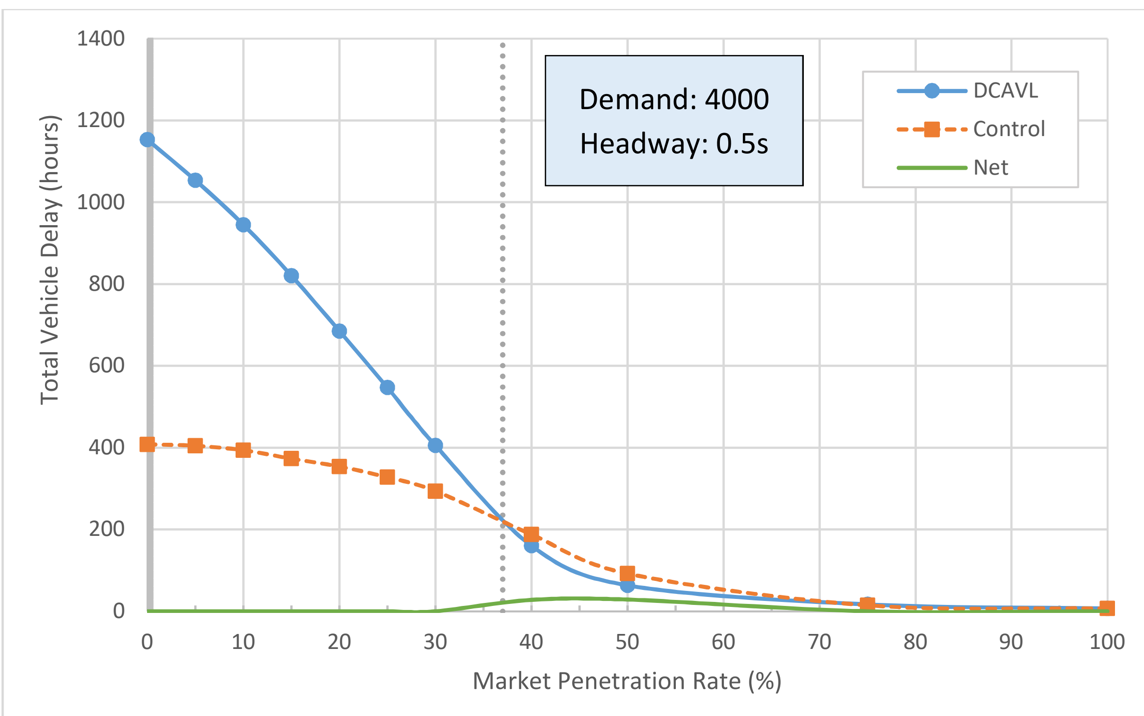


Figure 5. Results (4000 vehicles, 0.5 second headway)

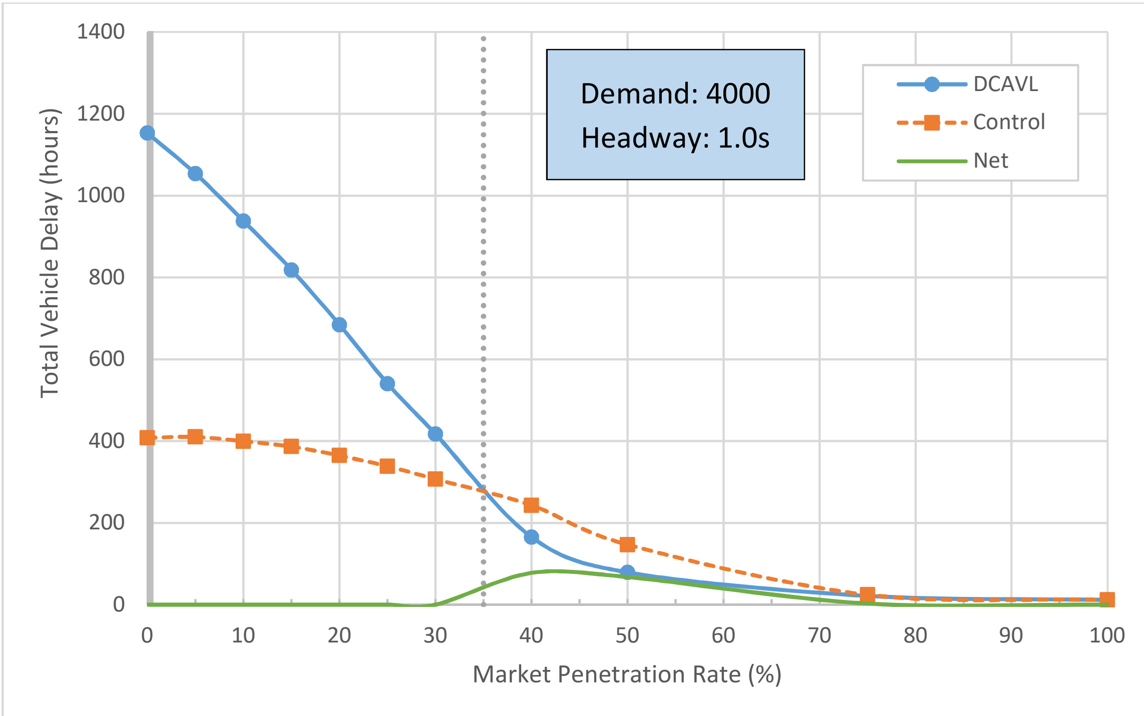


Figure 6. Results (4000 vehicles, 1.0 second headway)

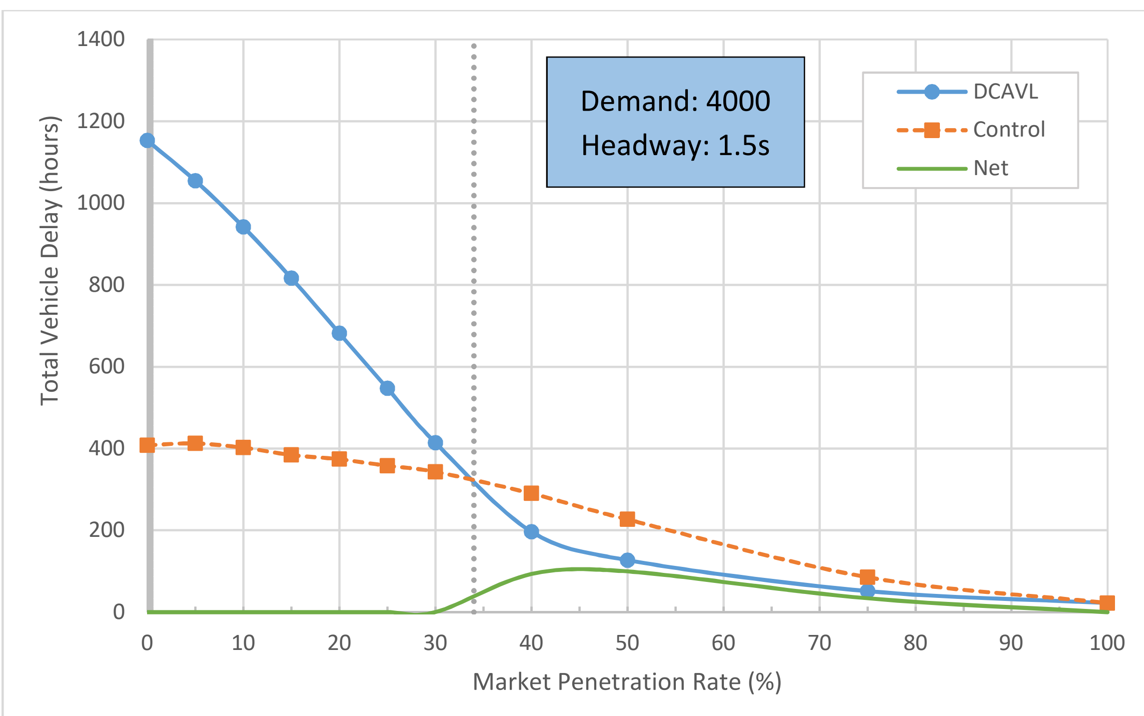


Figure 7. Results (4000 vehicles, 1.5 second headway)

The second group of figures shows the data collected from the three models with a demand volume of 5000 vehicles (Figures 8-10). In each of these models, the total vehicle delay begins at 0% MPR with 1911 hours for the experiment and 1153 for the control.

In the model with a 0.5 second CAV-CAV headway, the experiment begins to outperform the control at about 36% MPR with about 960 hours of total vehicle delay (Figure 8). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 15 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 212 hours.

In the model with a 1.0 second CAV-CAV headway, the experiment begins to outperform the control at about 35% MPR with about 1000 hours of total vehicle delay (Figure 9). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 27 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 235 hours.

In the model with a 1.5 second CAV-CAV headway, the experiment begins to outperform the control at about 34% MPR with about 1060 hours of total vehicle delay (Figure 10). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 181 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 207 hours.

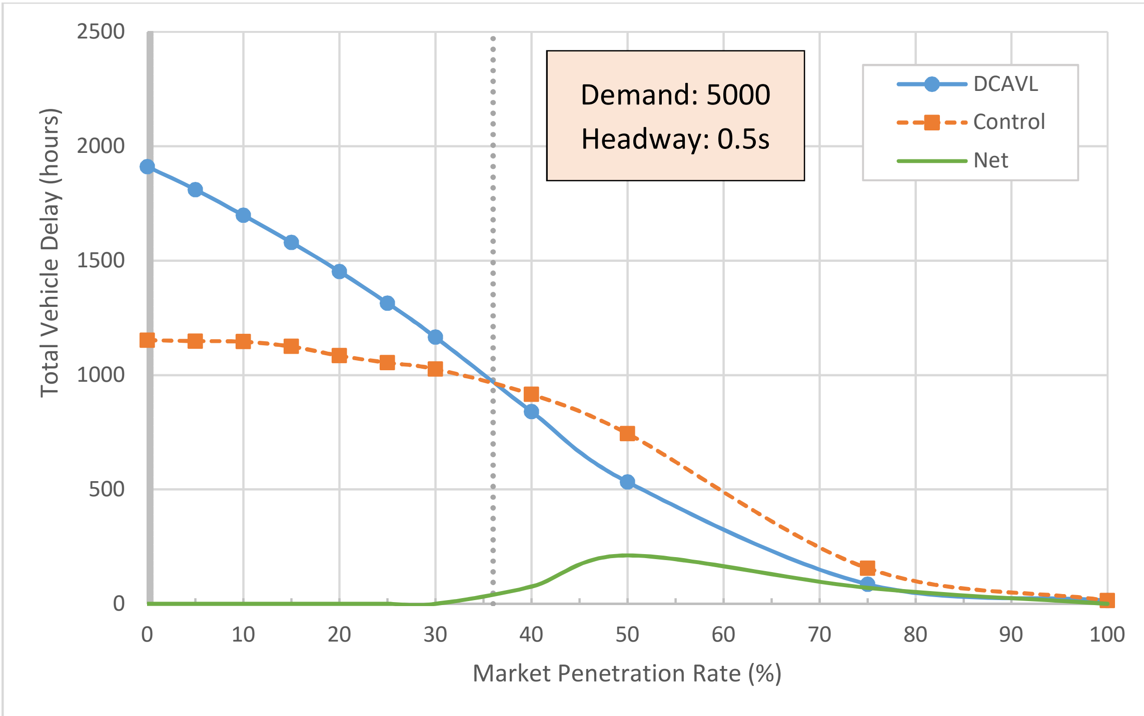


Figure 8. Results (5000 vehicles, 0.5 second headway)

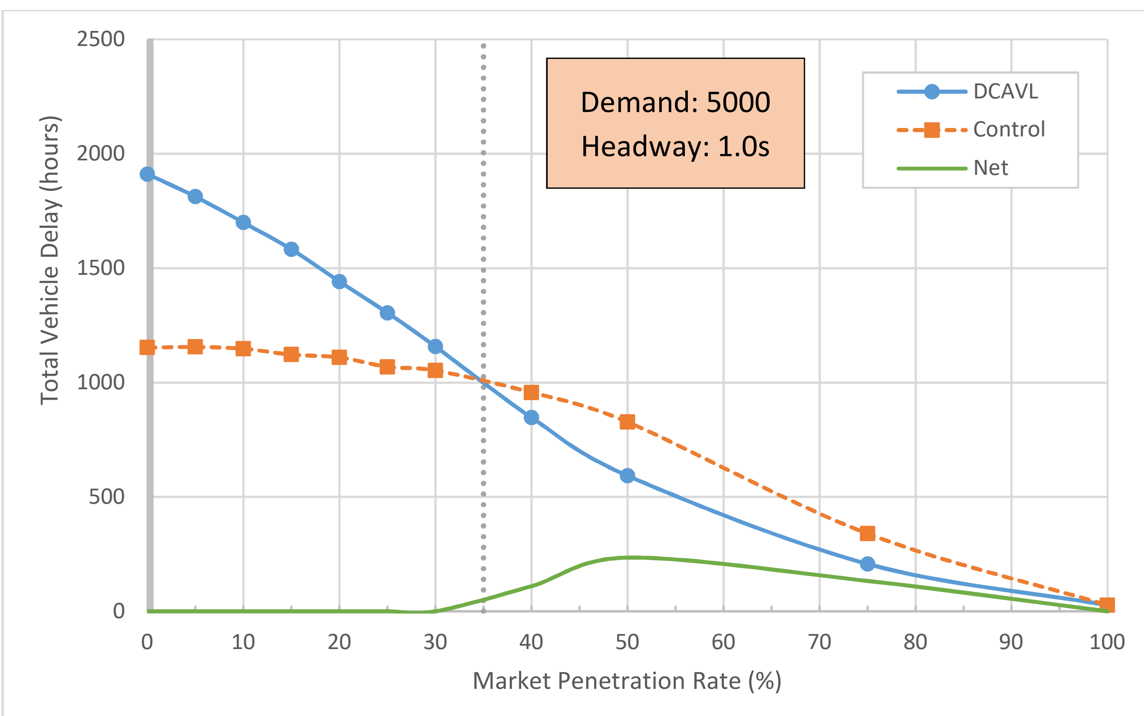


Figure 9. Results (5000 vehicles, 1.0 second headway)

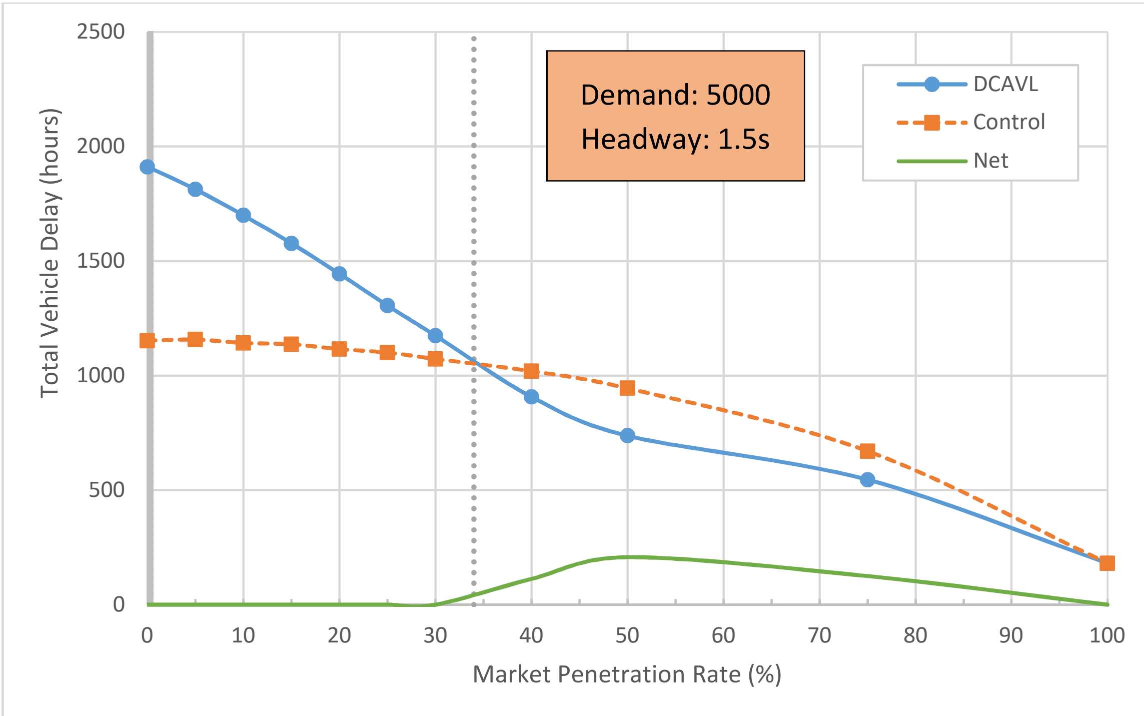


Figure 10. Results (5000 vehicles, 1.5 second headway)

The third group of figures shows the data collected from the three models with a demand volume of 6000 vehicles (Figures 11-13). In each of these models the total vehicle delay begins at 0% MPR with 2671 hours for the experiment and 1909 for the control.

In the model with a 0.5 second CAV-CAV headway, the experiment begins to outperform the control at about 37% MPR with about (00 hours of total vehicle delay (Figure 11). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 36 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 226 hours.

In the model with a 1.0 second CAV-CAV headway, the experiment begins to outperform the control at about 35% MPR with about 1770 hours of total vehicle delay (Figure 12). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 152 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 242 hours.

In the model with a 1.5 second CAV-CAV headway, the experiment begins to outperform the control at about 35% MPR with about 1800 hours of total vehicle delay (Figure 13). The experiment continues to outperform the control until the results from each lane scenario meet again at 100% MPR with 900 hours of total vehicle delay. The maximum benefit of the DCAVL occurs at about 50% MPR, where the gap in the total vehicle delay is about 201 hours.

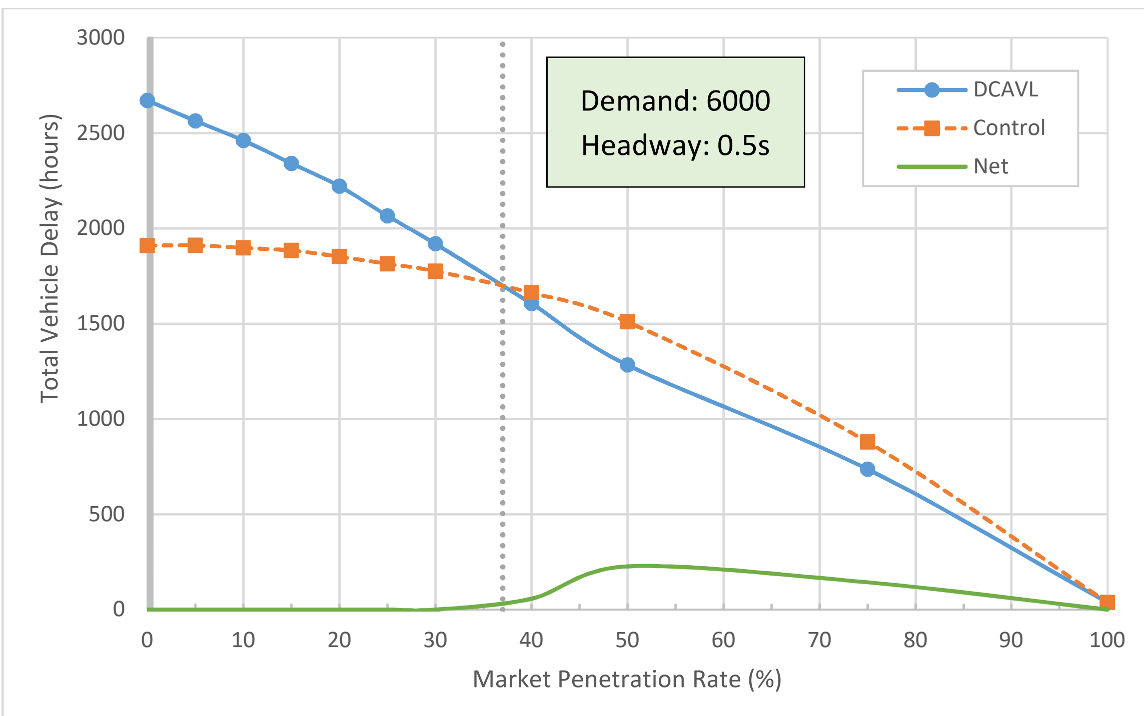


Figure 11. Results (6000 vehicles, 0.5 second headway)

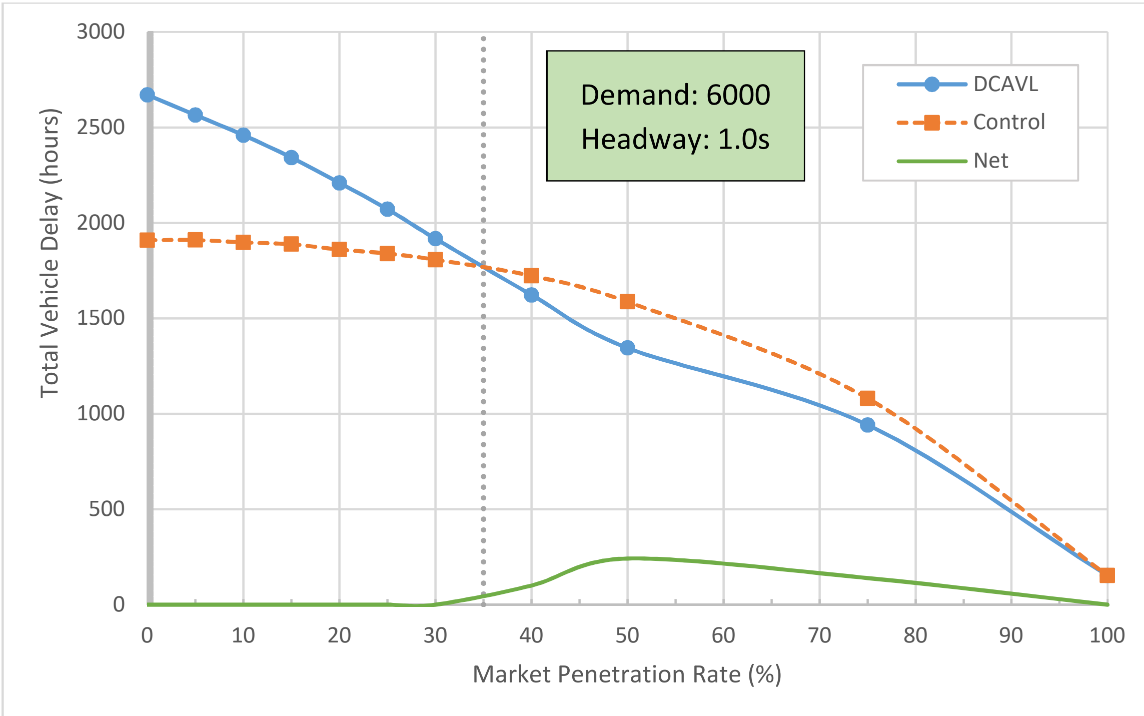


Figure 12. Results (6000 vehicles, 1.0 second headway)

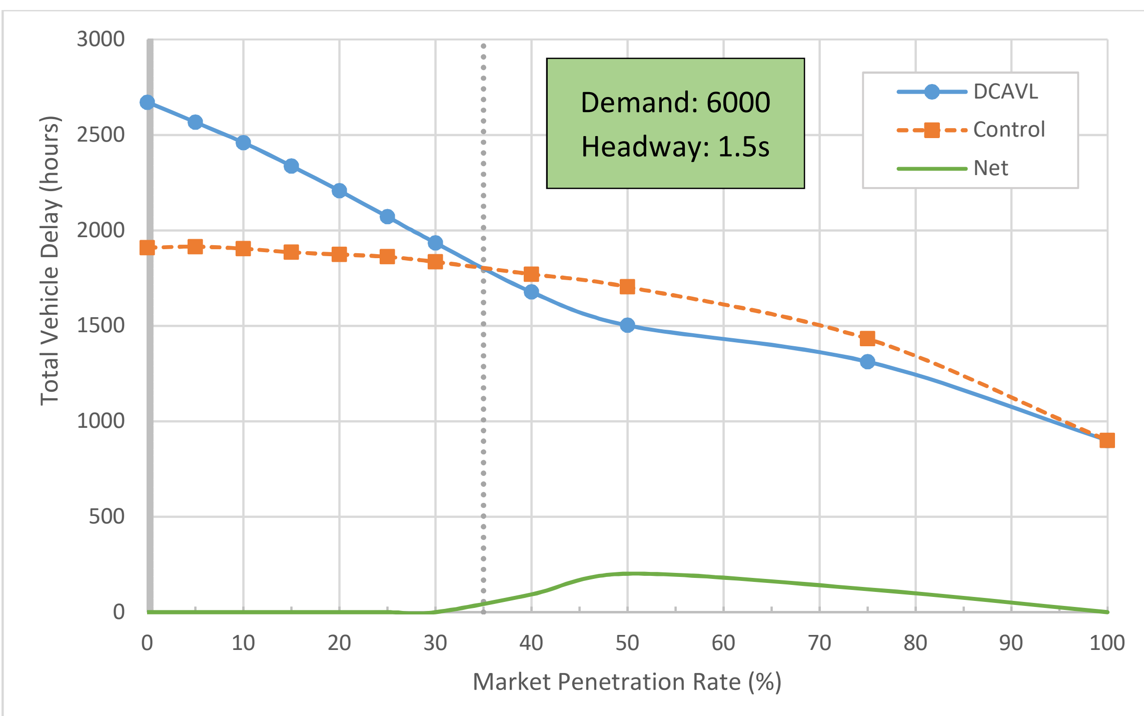


Figure 13. Results (6000 vehicles, 1.5 second headway)

The results of each model and its individual outperformance points are summarized in the table below (Table 3). Visually, the above graphs are shown compiled into one single figure below (Figure 14). All nine separate models show the outperformance of the experiment over the control at points between 34% and 37% MPR. After these points, the freeway with the DCAVL will continue to outperform the freeway without the DCAVL. The maximum benefit of the DCAVL consistently occurs between 42% and 50% MPR. Each of these regions are shown in the second graph below (Figure 15). The top group of lines represent the data from the scenarios with 6000 vehicles, the middle group represents the scenarios with 5000 vehicles, and the bottom group represents the scenarios with 4000 vehicles. Within each group, the experiment tends to start outperforming the control in the outperformance range and the gap between the lines maximizes in the maximum benefit range.

Table 3. Summary of Results

Model Parameters		**Outperformance Point (%)**	**Delay @ Outperformance (hours)**	**Max Benefit Point (%)**	**Delay Gap @ Max Benefit (hours)**
Demand	**Headway**				
4000 vehicles	0.5 sec	37	230	43	30
	1.0 sec	35	280	43	80
	1.5 sec	34	330	42	105
5000 vehicles	0.5 sec	36	960	50	212
	1.0 sec	35	1000	50	235
	1.5 sec	34	1060	50	207
6000 vehicles	0.5 sec	37	1700	50	226
	1.0 sec	35	1770	50	242
	1.5 sec	35	1800	50	201

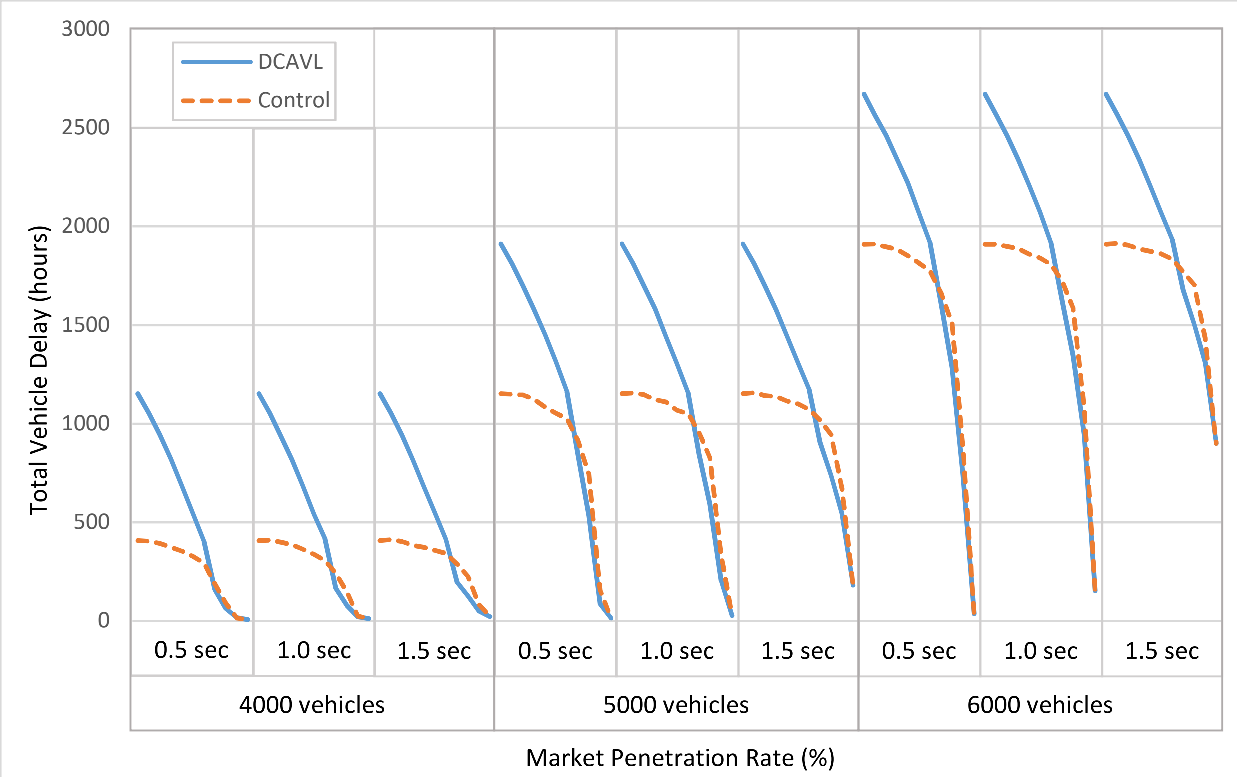


Figure 14. Compilation of Graphical Results

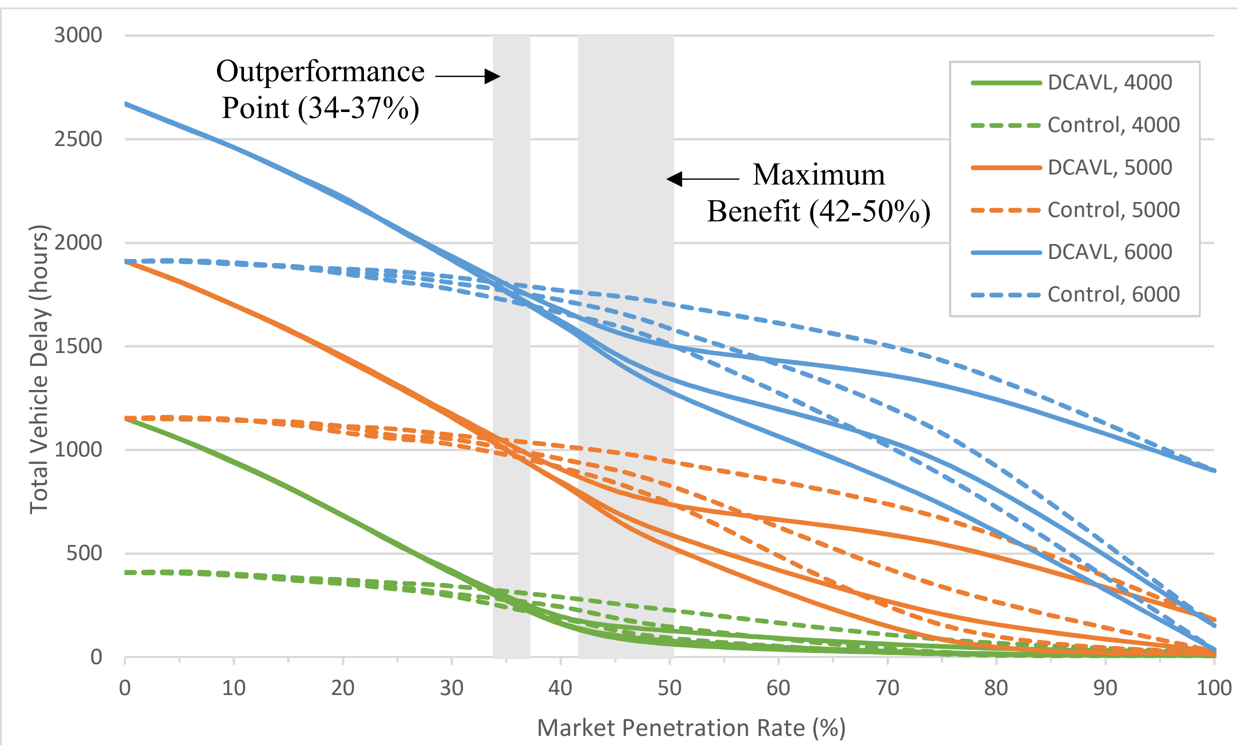


Figure 15. Graph Showing Points of Outperformance and Maximum Benefit

V. DISCUSSION

The data presented in the above section and its figures reveal that the total vehicle delay metric is drastically affected by the headway of the scenario. In contrast, the experiment begins to outperform the control between the MPRs of 34% and 37% regardless of the headway or demand volume of the model. Likewise, the maximum benefit of the DCAVL consistently occurs between the MPRs of 42% and 50%. These results are also largely independent of the headway or demand volume of the model.

These findings are extremely interesting for several reasons. First, it is evident that the total vehicle delay metric is greatly impacted by the demand volume of the model, but not the CAV-CAV headway. In the models with 4000 vehicles of demand, the maximum total vehicle delay of the experiment is 1153 hours. This value increases as the demand does. The models with 5000 vehicles of demand has a maximum total vehicle delay of 1911 hours in the experiment, and the models with 6000 vehicles of demand has a maximum total vehicle delay of 2671 hours. These results suggest that demand volume has a large impact on the total vehicle delay of the scenario and thus the performance of the roadway. These results are expected because additional vehicles on the road will incur additional total vehicle delay.

On the contrary, the CAV-CAV headway appears to have a very minimal effect on the total vehicle demand of the roadway. The results of each model with 4000 vehicles of demand are very similar to each other despite the CAV-CAV headway increasing from 0.5 seconds to 1.0 and 1.5 seconds. As shown in the compilation graph above, the results of the 3 models within each group of demand volume are almost identical. This strongly conflicts with the general consensus of most traffic engineers and researchers, some of whom have been cited in this paper. A. Ghiasi (3) (Ghiasi, Hussain, Qian, & Li, 2017), D. Farmer (Farmer, 2016), and M. Makridis (Makridis, et al., 2018) have all concluded that headway directly affects the performance of a roadway. The results of this scenario analysis seem to disagree with this conclusion.

Perhaps the most interesting is the fact the outperformance and maximum benefit points appear to be largely independent of both the CAV-CAV headway and the demand volume of the model. This is evidenced by the very tight range of MPRs that each of these points falls within. These results suggest that neither the CAV-CAV headway nor the demand volume has a significant impact on the performance of the freeway *with* the DCAVL in relation to the freeway *without* the DCAVL. This is interesting because the purpose of the DCAVL is to maximize the effects of CAV platooning (3, 12); thus, as the headway between CAVs decreases, the benefits of the DCAVL should increase and cause the outperformance point of the experiment over the control to be significantly lower. The results of this study contradict this hypothesis. Despite the varying CAV-CAV headways, the outperformance point remains in the very tight range of 34% to 37% MPR and even tends to increase as the headway decreases. Likewise, the maximum benefit points consistently occur in the range of 42% to 50% MPR regardless of the CAV-CAV headway.

An explanation for this lies in the extreme complexity of microsimulations and our transportation network they attempt to replicate. While basic traffic theory may suggest that the maximization of platooning between lower headway vehicles would increase roadway performance drastically, it is inconclusive whether this is true when considering more complicated aspects of our transportation system such as desired speed fluctuations, lane change dynamics, and vehicle following behavior. This paper is the first to consider all of these complexities when analyzing the effects of various potential headway and volume scenarios on DCAVL performance. As a result, current literature is unable to defend or oppose these results. A primary goal of this paper is to encourage future researchers to perform similar analyses to serve as refutations or validations of these results.

The results of this study reveal a trend in the outperformance of three-lane freeways with a DCAVL over that of traditional three-lane freeways. Under the default conditions presented in PTV Vissim 11.00-03, a basic three-lane freeway stretch is expected to benefit from one lane being allocated to a DCAVL starting around an MPR of 35% regardless of CAV-CAV headway and demand volume. The benefit of the dedicated lane is expected to maximize between an MPR of 42% and 50%. These results are very preliminary and are based on extremely limited data. However, they adequately provide a better understanding of the use of managed CAV lanes on three-lane freeways in various scenarios and can serve as a foundation for future researchers and traffic engineers to base their work upon.

VI. LIMITATIONS & FUTURE RESEARCH

There were several limitations in this study. First and foremost, the infancy of CAV technology makes accurate data difficult to collect and thus any related research agenda very speculative. The specific research enacted in this paper – the use of VISSIM to conduct a scenario analysis of the impacts of DCAVLs on freeway performance – is a topic that has not been addressed in current literature largely for this reason. The CoEXist team has provided the only current driving behavior model for CAVs that is integrated with Vissim (Sukennik, 2018). This recent development has served as a massive opportunity for researchers to begin creating complicated microsimulations involving CAVs. However, data limitations make this model practically impossible to calibrate or verify. For these reasons, the infancy of the technology has been a major limitation on this study.

Another limitation was the inevitable legal issues CAVs will face regarding the following of speed limits. As of right now, it is impossible to predict how legislature will be passed to resolve this issue. For the sake of this paper, CAVs were assumed to be allowed to exceed speed limits and thus would follow similar desired speed distributions as traditional vehicles. Whether this is realistic is unclear and unanswerable. Future researchers could easily face this limitation with an entirely different approach. Nonetheless, these legal issues presented distinct limitations on this study.

Some simulation-based limitations on this study also serve as potential avenues for future research to build upon this study. First, while there was both an entrance ramp and an exit ramp included in the site, this paper did not distinctly consider the impact of the weaving area on the results. The effects of the weaving traffic were incorporated into the overall results of the study; separating these results may offer a clearer analysis of the DCAVL's effects. Likewise, a site with additional weaving areas caused by multiple access points may develop very different results.

Another limitation was the omission of trucks and heavy vehicles from this study. Many roads have very significant amounts of truck and heavy vehicle traffic. Ideally, these would be included in analyses of DCAVLs because they have major impacts on roadway performance. This study did not consider the impacts trucks and heavy vehicles will inevitably have on a freeway in an attempt to maintain the simplicity of the analysis. It is unclear how many trucks and heavy vehicles will operate as CAVs; it is also unclear how these technologies will work on our transportation system. For these reasons, these extra layers of complexity were not included and thus were limitations on the study, but they could be considered by future researchers.

This study was also limited by the fact only fully automated vehicles were considered. As designated by the CoEXist team, the driving behavior used in the simulations was "AV_AllKnowing". This distinction implies the highest level of autonomy and connectivity, stated by CoEXist as having "profound awareness and predictive capabilities" (Sukennik, 2018). Partially automated and partially connected vehicles were not considered in this study. This could also be another basis for future research.

VII. CONCLUSION

Connected and Automated Vehicles (CAVs) offer several promising benefits to enhance the efficiency of our future transportation network, one of which is the potential to drastically reduce congestion by lowering the required safe following distance between consecutive vehicles. Because the headway between CAVs is expected to be lower than the headway between a CAV and a traditional vehicle, their benefits can be maximized by encouraging CAV platooning through a managed lane system such as a Dedicated Connected and Automated Vehicle Lane (DCAVL). This study used PTV Vissim microsimulation software to determine when a DCAVL would be beneficial to the overall performance of a three-lane freeway as measured by a total vehicle delay metric.

Due to the infancy of the CAV technologies, it is impossible to predict exactly how they will operate and thus one cannot conduct an analysis of just one specific scenario. As such, an extensive scenario analysis was conducted to examine the effects of a DCAVL within the scope of several input variables. The variables selected in this study were: the Market Penetration Rate (MPR) of CAVs, the CAV-CAV headway, and the demand volume. Given a scenario involving a realistic CAV-CAV headway and a three-lane freeway's demand volume, this research aims to answer the effects of a DCAVL at various MPRs. 198 unique scenarios were created; each were run in Vissim five separate times to create data from 990 different simulations to be analyzed.

The results overwhelmingly indicate that the conversion of one lane on a three-lane freeway to a DCAVL will begin to benefit the performance of the overall roadway between the MPRs of 34-37%. This effect will continue to improve until a maximum relative performance point between the MPRs of 42-50%, where the DCAVL will be the most beneficial. Interestingly, these results are consistent across each of the 9 primary models. This suggests that a DCAVL's benefit to a three-lane freeway is independent of the CAV-CAV headway and demand volume, despite demand having a very direct impact on overall roadway performance.

Although these results are very preliminary and are based on extremely limited data, they adequately provide a better understanding of the effects DCAVLs have on three-lane freeways under numerous different scenarios. As such, the results discussed in this paper can sufficiently serve as a foundation for future researchers and traffic engineers to base their work upon.

There are numerous directions future research can take to build upon this study and address the limitations discussed in the previous section. Various potential legislative outcomes could result in different scenarios for the following of speed limits. Several access points can be utilized to directly consider the effects of weaving on a DCAVL's performance. Trucks and heavy vehicles – potentially with CAV technology – could be considered to advance the realism of these simulations. Finally, various levels of autonomy and connectivity could be considered at different MPRs. By creating numerous different approaches for future researchers to build upon this study, this research has accomplished its goal of serving as a foundation for the analysis of scenarios involving CAVs and DCAVLs.

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