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Quantitative Evaluation of the Impacts of the Time Headway of Adaptive Cruise Control Systems on Congested Urban Freeways Using Different Car Following Models and Early Control Results

LINA ELMORSHEDY, BAHER ABDULHAI, AND ISLAM KAMEL

Department of Civil and Mineral Engineering, University of Toronto, Toronto, ON M5S 1A4, Canada

CORRESPONDING AUTHOR: L. ELMORSHEDY (e-mail: lina.elmorshedy@mail.utoronto.ca)

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ABSTRACT The impact of driving automation and adaptive cruise control (ACC) on traffic performance has been increasingly studied in recent years. This paper focuses on two widely used ACC car following models and investigates the impact of the time headway parameter on traffic operation and performance on one of the busiest freeway corridors in Ontario, Canada. Using Aimsun microsimulation, we compare two commonly used ACC car following models; the intelligent driver model (IDM) and Shladover's model which has been recently adopted in Aimsun Next 20. Several experiments have been conducted to evaluate the freeway performance for different desired headway settings and market penetration rates of ACC-equipped vehicles. Simulations results confirm the reported IDM drawbacks of having a slow response leading to headway errors which are less pronounced with Shladover's model thereby leading to more accurate quantification by the latter. This study further presents a simple on-off ACC-based traffic control strategy which aims to adapt in real time the driving behavior of ACC-equipped vehicles to the prevailing traffic conditions so that freeway performance is improved. The simulation results demonstrate that, even for low penetration rates of ACC vehicles, the proposed control concept improves the average network throughput, delay, and speed compared to the case of only manually driven or uncontrolled ACC vehicles.

INDEX TERMS Adaptive cruise control systems, traffic control, traffic modeling.

I. INTRODUCTION

AUTOMOBILE manufacturers, as well as numerous researchers, have been devoting significant efforts to the development of Advanced Driver Assistance systems (ADAS). The next step in the development of ADAS is to incorporate Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication capabilities representing Connected and Automated Vehicles (CAVs) which would undertake vehicle functions and ease the driving task further. Improved vehicle operation, in terms of enhanced safety and increased passenger convenience, has been the prime motivator behind CAVs development, in addition to reducing the negative environmental effects of transportation. CAV systems are expected to alter the capabilities of individual vehicles within the next decades for the benefit of their own drivers, which may not be beneficial to the overall traffic conditions if such systems are only serving the convenience of their individual users in a myopic way. The introduction of CAVs will, therefore, transform the future of transportation, and there is a need to quantify the effect of such technologies on congested urban transportation systems and potentially steer their effect in a positive direction by implementing appropriate traffic control strategies.

One of the first candidate systems that will affect the traffic flow dynamics is the Adaptive Cruise Control (ACC) system [1], being one of the mature vehicle automation

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technologies emerging in the market in the past few years. ACC is an extension of the conventional Cruise Control (CC) system which is known to automatically maintain the speed of the vehicle to a certain value set by the driver. The ACC system uses headway sensors to continuously measure the spacing to the vehicle ahead and adjusts the vehicle speed to ensure this headway is maintained close to a desired value. Cooperative Adaptive Cruise Control (CACC) systems represent a more sophisticated form of ACC by incorporating communication such that the equipped vehicles communicate and coordinate their speed changes to one another, resulting in less detection and response delays and permitting closer vehicle following [2]. The use of conservative parameter values for such systems may enhance one's convenience and safety, but at the same time, it would affect the transportation network performance, potentially negatively [3].

While most research is focusing on the technology side of vehicle automation, there is comparatively a smaller number of studies focusing on quantifying the effect of such systems on traffic performance. In this context, literature studies have been divided into studies focusing mainly on the stability of such systems, as in [4] and references therein, showing that connected and autonomous vehicles can improve the string stability of traffic flow and increase throughput, however, such studies assume minimal reaction times that are only attributable to sensing and mechanical delays as well as minimal headways guaranteeing basic safety, thereby adopting a futuristic best-case scenario. Other studies focus on their effect on speeds and delays without looking into the stability issue such as [5]–[13] which used microscopic simulation studies to quantify the impact of ACC/CACC on traffic performance under different time headway settings and penetration rates and are more in line with the scope of our work. The key conclusions drawn from these studies are that ACC systems can potentially improve or worsen the transportation network performance depending on their parameter settings, i.e., time headway, acceleration and deceleration, and their penetration rate.

Ntousakis *et al.* [10] have shown that the desired time headway setting in ACC systems has an impact on the roadway capacity since smaller time headway settings led to higher capacity. The study has also shown that as the ACC penetration rate increases, the capacity further increases if the time headway is less than 1.20 sec, while capacity decreases with longer time headways ($\geq$1.2 sec) and increased ACC penetration rates. However, this study [10] assumes operating in ideal conditions in which the network used for simulations is a single-lane stretch without any bottlenecks, thereby achieving the maximum capacity of the road for each investigated headway setting, i.e., $\sim$3600 veh/hr for 100% ACC vehicles with 0.8 sec headway, representing a best case scenario. The authors in [11] and [12] go a step further by analyzing the effects of ACC on a real freeway stretch showing that ACC systems will lead to significant deterioration in the network's performance. However, the scenarios considered in these studies assume the adoption of conservative headway settings by all ACC users representing a worst case scenario, in addition to assuming small reaction times for such systems and adopting Shladover's first introduced ACC car following model in [13] before introducing their latest ACC model complemented with field studies.

In [13], the effects of ACC and CACC-equipped vehicles on highway capacity have been estimated using microscopic simulation. The time headway settings for the ACC-equipped vehicles ranged from 1.1 sec to 2.2 sec, while it ranged from 0.6 sec to 1.1 sec for the CACC-equipped vehicle systems. The results showed that CACC systems can increase the traffic capacity for moderate to high penetration rates, while ACC systems are unlikely to produce significant improvements to the capacity of highways. Besides the time headway, another parameter that is being overpassed in ACC quantification studies is the reaction time, which is defined as the time it takes a vehicle to react to the speed changes of the preceding vehicle [14]. It is a common assumption that automated vehicles will have negligible reaction time compared to what human drivers can achieve. However, recent studies [15], [16] show that the reaction times of ACC systems range between 0.8-1.2 sec, which is similar to what is commonly found for human drivers. In [17] the existing literature on the effects of CAVs is summarized and policy recommendations are given based on the reviewed studies.

The main contributions of this work are as follows:

- Quantifying the effects of ACC systems on the transportation network performance in the context of a long and congested urban freeway corridor with multiple bottlenecks and hotspots. Different headway settings representing a best case, worst case and a range headway representing different driver choices are considered in this study, all under realistic reaction time settings.
- Choosing the most suitable car following model for ACC representation by adopting two commonly used ACC car following models from the literature. The adoption of different car following models for ACC representation in this work is to first observe the general performance trends resulting from both models and to highlight the shortcomings of any based on real traffic simulations.
- Enabling a positive transformation with the advent of such systems by implementing a simple traffic control strategy which aims to adapt the time headway of ACC-equipped vehicles in real time so that freeway traffic flow efficiency is improved as a first step and subject to further enhancements by looking into additional performance metrics such as safety, stability, emissions, etc.

In this work, we develop a driving-automation-enabled dynamic simulation model of the Queen Elizabeth Way (QEW) in Ontario, Canada during the AM peak period, using Aimsun traffic microsimulation platform.

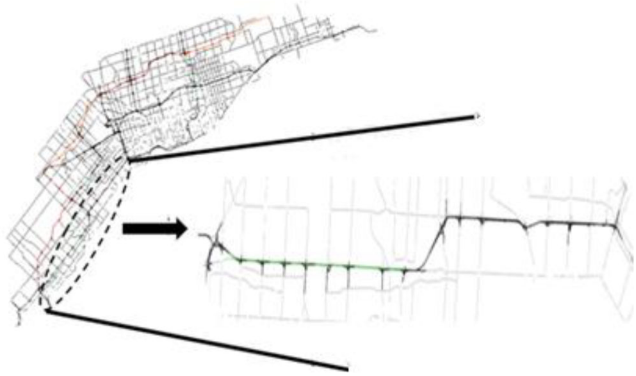

FIGURE 1. Area Under Study.

II. CASE STUDY (NETWORK DESCRIPTION)

The area under study focuses on the eastbound direction of the QEW and parallel service roads, one of the busiest freeway corridors in Ontario, Canada, in the morning peak (6:00-10:00 AM). The network extends between Hamilton-Burlington borders on the west to the City of Toronto on the east side for 45 km. The area under study is extracted from a larger Aimsun simulation model covering most of the Greater Toronto Area (GTA). A detailed description of the GTA model is presented in (15). Fig. 1 shows the area under study as a subnetwork of the GTA model. The simulation model was manually calibrated and validated using real traffic data so that it can reproduce the typical traffic conditions of the examined motorway. Demand data were extracted from the Transportation Tomorrow Survey and larger traffic assignment models at the University of Toronto (16). Two different ground-truth data sources were used to calibrate and validate the microscopic model of QEW; the vehicle counts and speeds from loop detectors installed on the QEW, and speed observations retrieved using Google Directions API. The two sources were used together to prepare a ground-truth dataset of counts and speeds over the QEW stretch to calibrate and validate the simulation results.

A. NETWORK CALIBRATION

Multiple measures were used to validate the simulated speeds and counts using the observed ones. The counts are evaluated using the GEH statistic [18] which is an empirical formula used in comparing traffic flows and is defined as follows:

$$GEH = \sqrt{\frac{2(M-C)^2}{M+C}}, \tag{1}$$

where M and C are the simulated and observed flows, respectively. Other visual tools were used in comparing simulated and observed quantities, such as time-space speed diagrams, scatter plots, and traffic flow fundamental diagrams, which are omitted here for brevity. The calibrated parameters include a global adjustment factor of the full demand in addition to a custom adjustment at specific locations. They also include global parameters related to driving behavior and simulation configuration, such as merging distances over freeways, acceleration, deceleration, and the reaction time of vehicles. The final calibration results show that the average GEH statistic at 43 detectors installed over the QEW for the entire morning peak (four hours) is equal to 4.9 with 91% of the points with GEH less than 10 and 56% of the points with GEH less than 5. Further, the average GEH calculated at the 43 detector locations for the four 1-hr intervals is equal to 5.9 with 87% of the points with GEH less than 10 and 49% of the points with GEH less than 5. Moreover, we were able to reproduce the two major eastern and western congestion hotspots for the correct time period and extent as will be outlined later in the results section and achieved an average root mean square error (RMSE) of speeds equal to 0.24. Finally, we adopted the simplest case scenario in this study in which all drivers behave similarly and are assigned similar parameter values throughout the simulation. This is done mainly to emphasize the focus only on quantifying the effect of introducing new ACC models to the system without adding other complexities. However, a possible extension after analyzing such effects is to add heterogeneity to the system similar to the work in [19].

III. SIMULATION ENVIRONMENT

A. AIMSUN MICROSCOPIC SIMULATOR

The implementation of ACC in traffic simulators is possible by overriding the default vehicle behavioral models and applying suitable ones for ACC. In this work, the microscopic simulator Aimsun is used to model ACC and perform the corresponding simulation scenarios. Aimsun includes the MicroSDK tool [20], which enables overriding its vehicle behavioral models and applying external behavioral models, programmed in C++, to the microsimulation environment. Aimsun also includes the Aimsun API tool, which can be used to extend the functionalities of the basic Aimsun simulation environment by including user-defined applications. In this work, we used the MicroSDK tool, to include new ACC models, and the API tool to implement traffic control functions with ACC.

B. AIMSUN DEFAULT CAR FOLLOWING MODEL

The default car following model implemented in Aimsun is based on the empirical Gipps model [19], [20] in which the model parameters are not global but determined by local parameters that depend on vehicle and driver characteristics. The Gipps model in Aimsun consists of two speed components: an acceleration and a deceleration component. The acceleration component describes the maximum speed a vehicle n can achieve during a time period (t, t + T), and is given by:

$$\dot{x}_a(n, t+T) = \dot{x}(n, t) + 2.5\,\ddot{x}(n)T\left(1 - \frac{\dot{x}(n, t)}{\dot{x}^*(n)}\right) \times \sqrt{0.025 + \frac{\dot{x}(n, t)}{\dot{x}^*(n)}}, \tag{2}$$

where $\dot{x}(n,t)$ is the speed of vehicle n at time t, $\ddot{x}(n)$ is the maximum acceleration for vehicle n, T is the reaction time of the vehicle and $\dot{x}^*(n)$ is the desired speed of vehicle n. On the other hand, the deceleration component describes the maximum speed that the same vehicle n can reach during the same time interval (t, t + T), while in car following mode, i.e., according to its own characteristics and the limitations imposed by the presence of a leader vehicle, and it is given by equation (3), as shown at the bottom of the page, where $d(n)$ is the maximum deceleration desired by vehicle n, $x(n,t)$ is the position of vehicle n at time t, $x(n-1,t)$ is the position of the preceding vehicle $n-1$ at time t, $s(n-1)$ is the effective length of vehicle $n-1$, and $d^{'}(n-1)$ is an estimation of the desired deceleration of vehicle $n-1$. The final speed for vehicle n during a time interval $(t, t+T)$ is the minimum of these two speeds. The manually driven vehicles in this study follow Aimsun's default Gipps model. It is worthy to highlight that the Gipps model does not have an explicit representation of the desired time headway to be achieved by the vehicles, which is an important parameter when modelling ACC systems.

IV. SIMULATION EXPERIMENTS

Several simulation experiments have been conducted for different ACC car following models, desired headway settings, and penetration rates of ACC-equipped vehicles to quantify their effect on the performance of the network. The tested scenarios include penetration rates of ACC vehicles of the values of 0% (base case), 25%, 50%, 75%, and 100%. Whereas the investigated time-headways are: (1) 0.8 sec (being the minimum headway for ACC), (2) 2.0 sec (the common default value recommended by manufacturers), and (3) a normally-distributed headway ranging between [0.8, 2.0] sec with an average of 1.2 sec (representing a range of settings selected by different drivers).

Since the main focus of our study is to quantify the effect of the time headway parameter of ACC systems, therefore, the car following model parameters that are found in common between ACC vehicles and human driven vehicles, i.e., maximum acceleration, comfortable deceleration, desired speed, jam distance, etc., are assumed to have the same mean values to ensure traffic homogeneity. Moreover, all ACC car following model parameters are chosen to be within suitable ranges found from the ACC calibration studies in the literature as in [16] and [23]. In all simulation scenarios we assume that the reaction time of the ACC-equipped vehicles is equal to that of the manually driven vehicles which was found to be equal to 1.1 sec as a result of the network calibration. The reaction time is not an explicit parameter in the car following model used but rather a parameter adjusted via Aimsun traffic microsimulator, which is defined as the time it takes a driver/vehicle to react to the speed changes of the preceding vehicle and it must be equal to multiples of the simulation step which is set to 0.1 sec in this work.

We investigated two of the most commonly used car following models with ACC systems which are (1) the Intelligent Driver Model (IDM) that has been adopted in several ACC quantification as well as calibration studies [15], [16], [19], [23]–[29], and (2) the car following model developed by Milanes and Shladover in [24] which was developed based on experimental field studies and implemented in Aimsun Next 20 as the default ACC car following model and which we will refer to here as Shladover's car following model. These models represent the two main ACC quantification scenarios considered in the simulation experiments. Scenario (1) considers an IDM-based ACC while scenario (2) considers a Shladover-based ACC. For all scenarios, the average network throughput, delay, and speed are used to assess the performance of the network. Five replications were carried out for each experiment per examined scenario to take into account the stochastic nature of the simulations, and the average values of the performance metrics are compared.

A. SCENARIO (1): IDM-BASED ACC

In this scenario we assume that the ACC vehicles move according to the IDM model, introduced by Treiber and Kesting [25]. This model was suggested by Kesting *et al.* [26], as suitable for modeling ACC equipped vehicles. Many studies, e.g., [23]–[29], have used IDM as the car following model for ACC vehicles. The IDM calculates the vehicle's acceleration based on the following equation:

$$\dot{v}(s, v, \Delta v) = a\left[1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right], \tag{4}$$

where a is the maximum acceleration, v is the current speed, v_0 is the desired speed, s is the actual distance to the preceding vehicle and $s^*(v, \Delta v)$ is the desired distance which is calculated as follows:

$$s^*(v, \Delta v) = s_0 + \max\left(0, vT_d + \frac{v\Delta v}{2\sqrt{ab}}\right), \tag{5}$$

where s_0 is the jam distance (minimum distance required between two vehicles when stopped), T_d is the desired time headway, and b is the comfortable deceleration. The IDM algorithm has then been coded in C++ and included as an external behavioral model in Aimsun. The parameter values used in IDM-based ACC are listed in Table 1.

$$\dot{x_b}(n, t+T) = d(n) + \sqrt{d(n)^2T^2 - d(n)\left[2\{x(n-1,t) - s(n-1) - x(n,t)\} - \dot{x}(n,t)T - \frac{\dot{x}(n-1,t)^2}{d'(n-1)}\right]}. \tag{3}$$

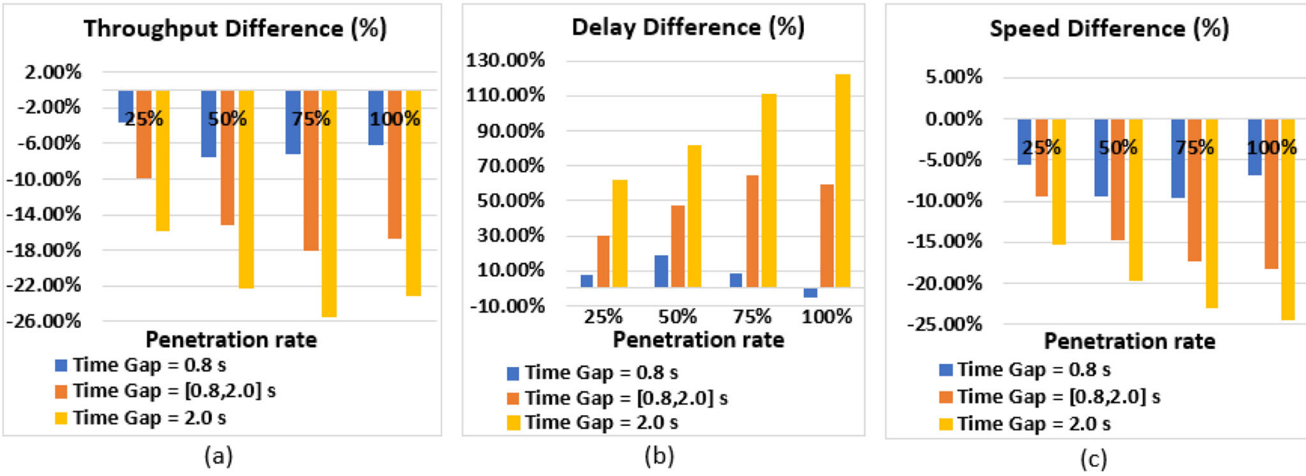

FIGURE 2. (a) Average throughput (b) Average delay (c) Average speed differences compared to the base case for IDM-based ACC systems.

TABLE 1. Parameter values for IDM.

Parameter	Value
a	$2\ m/s^2$
b	$3\ m/s^2$
v_0	$100\ km/hr$
s_0	$1\ m$
δ	4
T_d	3 different headways (1) 0.8 sec, (2) 2.0 sec and (3) Range between 0.8s and 2.0s

IDM-based ACC Simulation Results: For the full freeway stretch, we present the average throughput, delay and speed differences compared to the base case, i.e., the case with no ACC vehicles, for the different headway settings considered in Fig. 2. It is observed that the throughput, delay and speed deteriorated compared to the base case for all the investigated headway settings. Such deteriorations increase as the desired time headway increases, as well as when the penetration rate increases, within a headway setting, which is more significant for the 2.0 sec and the [0.8, 2.0] sec headway settings. The results show that the throughput, delay and speed can deteriorate by up to 26%, 122% and 25% respectively if all ACC users on the road adopt the default 2.0 sec headway recommended by auto manufacturers. While when users pick a headway setting randomly from the range of the admissible headways the throughput, delay and speed deteriorate by up to 18%, 64% and 18% respectively.

Unexpectedly, deteriorations were also observed for all performance metrics even when all ACC users adopted the minimum admissible headway, i.e., 0.8 sec, which motivated us to further investigate the IDM car following dynamics and determine whether the model achieves the desired headways or not.

IDM Car Following Dynamics: By observing the IDM acceleration given in equation (4), we notice that IDM has two operational modes mimicking the basic behavior of ACC systems: (1) a cruising mode for free flow traffic situations in which the applied acceleration is represented by: $a[1 - (\frac{v}{v_0})^4]$, where the lead vehicle, if any, is out of range of the subject vehicle, and (2) a car following mode in which the acceleration to be applied is represented by: $a[1 - (\frac{v}{v_0})^4 - (\frac{s^*(v,\Delta v)}{s})^2]$, and is mainly influenced by the presence of a lead vehicle. The detection range is implicitly included in the model since when the actual spacing, s, is large the quantity $(\frac{s^*}{s})^2$ will be small enough to not significantly contribute to the IDM acceleration $\dot{v}(s, v, \Delta v)$.

In addition to the unexpected performance of IDM based on our simulation results, it has also been reported in the literature [24] that the troubling behavior of the IDM is mainly reflected in the delayed response to speed changes by the leading vehicle resulting in a time-gap error even in stationary car following situations, both of which motivated us to investigate this issue further. In steady state traffic conditions, we have $\dot{v}(s, v, \Delta v)$ and Δv equal to zero; hence, from (4) and (5) we get,

$$1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s^*}{s}\right)^2 = 0 \tag{6}$$

$$s^* = s_0 + vT_d. \tag{7}$$

Therefore, in steady state conditions, the achieved steady state distance spacing s_{ss} between two vehicles is given by,

$$s_{ss} = \frac{s^*}{\sqrt{1 - \left(\frac{v}{v_0}\right)^4}} = \frac{s_0 + vT_d}{\sqrt{1 - \left(\frac{v}{v_0}\right)^4}} \tag{8}$$

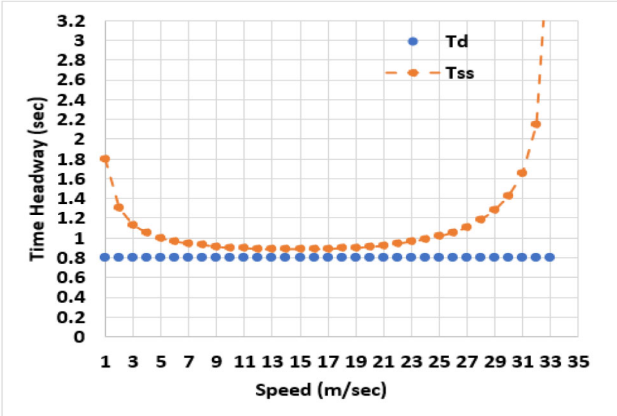

FIGURE 3. Desired and achieved time headways in steady state traffic conditions from IDM car following.

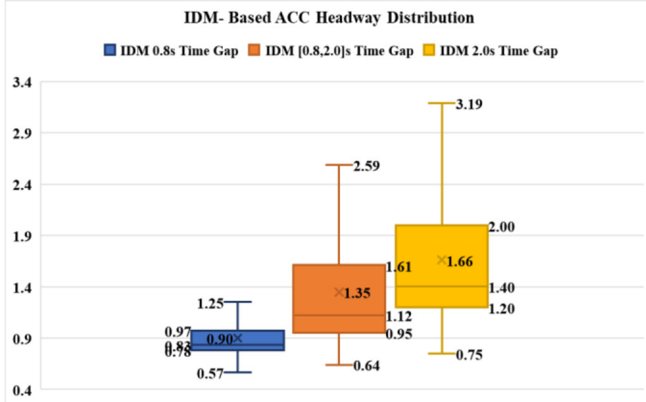

FIGURE 4. Distribution of the average headways for the different time headway settings for IDM-based ACC.

and the corresponding achieved steady state time headway T_{ss} is given by,

$$T_{ss} = \frac{s}{v} = \frac{\frac{s_0}{v} + T_d}{\sqrt{1 - \left(\frac{v}{v_0}\right)^4}}. \tag{9}$$

The graph of equation (9) is shown in Fig. 3 (for $s_0 = 1\ m$, $T_d = 0.8\ sec$, $v_0 = 33.33\ m/sec$) and indicates that T_{ss} is always higher than T_d which is obvious especially for high and low speed ranges, and this is mainly for the following reasons:

- For low speeds, the minimum distance, s_0, leads to differences between T_{ss} and T_d which increase further as the speed decreases. The difference between T_{ss} and T_d is obvious for speeds lower than 7 m/s.
- For high speeds, this difference is because of the term $\sqrt{1 - (\frac{v}{v_0})^4}$ particularly for speeds higher than 23 m/sec. However, this speed range implies free flow traffic and thus most inter vehicle spacings are longer than the desired spacings since cars are less likely to be in the car following mode.
- For speeds between 7 m/sec to 23 m/sec, which is most likely the speed range for steady state traffic in real-world scenarios, the steady state time headway achieved is almost constant at around ≈0.9 sec. This implies a headway error. What we prove here mathematically is in line with field observations reported in in [23] and [24], confirming this drawback of IDM. But at the same time, we show that the IDM model still conserves the basic property of the constant time headway (CTH) policy, which has been widely employed as the spacing policy in modern ACC systems; that is achieving a constant time headway at different equilibrium speeds within the speed window of 7-23 m/sec.

The IDM headway error reported in [19] was a result of the field tests performed using a few ACC cars to develop a more robust ACC car following model and our study complements this by investigating the headway materialization of IDM-based ACC on a full-length calibrated real freeway stretch. Therefore, it is confirmed that the IDM's achieved time headway will almost always be higher than the desired time headway in steady state traffic conditions for the whole speed range. This raises a sequel question about the materialization of the desired headways in unsteady state traffic, and thus motivated us to examine the achieved headways in our case study network given the high demand and the congested traffic conditions observed.

Average headways (calculated every 15 minutes) are collected at each detector location along the QEW freeway for the entire simulation period. The side-by-side box plots in Fig. 4 show the distribution of the average achieved headways on the QEW highway stretch for the 0.8 sec, the [0.8, 2.0] sec, and the 2.0 sec headway settings. As shown in Fig. 4, the average achieved headways are 0.9 sec and 1.35 sec for the 0.8 sec and the [0.8, 2.0] sec headway settings, respectively, which implies that the achieved headways are slightly higher than the desired headways. This headway error may explain the deteriorations in all performance metrics observed even with all ACC vehicles adopting the minimum headway setting which emphasizes the headway error drawback of the IDM car following due to its slow response as previously outlined. For the 2.0 sec headway setting, the average achieved headway is 1.66 sec which is lower than the desired headway and this is mainly attributed to exacerbated congestion caused by adopting such long desired headways in an already congested network due to the high demand during the morning peak. It is obvious that congestion increased significantly when all ACC users adopted the 2.0 sec headway setting since the average delay increased by around 122% at 100% penetration as shown in Fig. 2b which is hindering the materialization of such long headways.

Therefore, despite the popularity of the IDM model in the literature as an ACC car following model, we have found that the main troubling behavior of IDM is reflected in the headway error due to its slow response to the lead vehicle speed variations. This is important to note since our main goal in this work is to first quantify the impacts of ACC systems especially in a worst-case scenario setting, i.e., all users adopting the maximum admissible headways. Our second goal is to introduce simple control algorithms, to reduce the deteriorations caused by using conservative ACC system parameters, by imposing shorter headways when needed aiming at reducing congestion and improving the network performance. This necessitates the capability of the used ACC model to follow the desired model parameters to the extent possible to achieve the anticipated benefit from the exploitation of such systems. Therefore, in the rest of the work we base our ACC quantification and control described in the following sections on the car following model developed by Shladover which is proven to have a faster response compared to IDM and a lower headway error according to the experimental field studies in [24]. Hence, it is a more suitable car following model representative of the time headway parameter, which is the focus of our work, first to quantify its' effect and second to be used in traffic control for enhancing the network performance as will be presented later in the paper.

B. SCENARIO (2): SHLADOVER-BASED ACC

This scenario assumes that the ACC vehicles move according to the ACC algorithm described in Milanés and Shladover [24]. We chose this model since it was formulated based on real field-test experiments and had a faster response thus a smaller headway error compared to IDM [24]. It is also conveniently implemented as a default ACC car following model in the traffic microsimulator used in this work, i.e., Aimsun Next 20. This ACC controller will determine the speed based on the two range parameters: the lower detection threshold and the upper detection threshold which are set in Aimsun by default to 100 m and 120 m respectively. When the gap between a subject vehicle and its preceding vehicle is larger than the upper threshold, then the preceding vehicle is beyond the on-board sensors' detection range and the controller will apply the speed regulation control mode, applying acceleration a_{sv} to reach the free-flow speed as follows:

$$a_{sv} = k_1\left(v_f - v_{sv}\right) \tag{10}$$

where v_f is the free-flow speed, and v_{sv} is the current speed of the subject vehicle. If the gap is smaller than the lower threshold, the controller will use the gap regulation control mode, to help the subject vehicle follow the preceding vehicle as follows,

$$a_{sv} = k_2(x_l - x_{sv} - t_{hw}v_{sv}) + k_3(v_l - v_{sv}) \tag{11}$$

where x_l and x_{sv} are the current positions of the leading and the subject vehicle respectively, t_{hw} is the desired time headway, and v_l is the current speed of the preceding vehicle. The gap regulation control mode component consists of two parts; the first part controls the gap itself ("gap component") between the following vehicles and the second part controls the speed difference between them. The k values are the gains on both the position and speed errors. When the gap is between the two thresholds, the controller will maintain the car following mode the vehicle used in the previous time step which is mainly to prevent frequent shifting between the two control modes, and thus creating a smooth speed profile. The parameter values used in IDM-based ACC are listed in Table 2.

TABLE 2. Parameter values for shladover's model.

Parameter	Value
a	$2\ m/s^2$
v_f	$100\ km/hr$
T_d	3 different headways (1) 0.8 sec, (2) 2.0 sec and (3) Range between 0.8s and 2.0s
$k_1,\ k_2,\ k_3$	Default values in Aimsun as a result of model calibration in [24]

Shladover-based ACC Simulation Results: We present the average throughput, delay and speed differences compared to the base case for the different headway settings in Fig. 5. It is observed that the throughput, delay, and speed deteriorated compared to the base case for the 2.0 sec headway setting and such deteriorations increase as the penetration rate increases. While when the time headway setting decreases, improvements in throughput, delay and speed are achieved. The performance results in Fig. 5 show that as the penetration rate of the ACC vehicles with the [0.8–2.0] sec and the 0.8 sec time headway settings increases, higher speeds and throughputs and lower delays can be achieved.

The results show that the throughput, delay, and speed can deteriorate by up to 20%, 110% and 24% respectively if all ACC users on the road adopt the default 2.0 sec headway recommended by automanufacturers. Such huge deteriorations were also observed in the IDM-based ACC performance results presented in Fig. 2. This implies that adopting such a conservative headway setting will lead to performance degradation, since human drivers can generally achieve shorter headways on average [30]. While when users pick a headway setting randomly from the range of the admissible headways the throughput, delay and speed improve by up to 2%, 16% and 6% respectively. Moreover, the average throughput, delay and speed could be improved by up to 3%, 34% and 18% respectively, if the ACC vehicles adopt a 0.8 sec time headway. The main difference between Shladover-based ACC and IDM-based ACC results as illustrated in Figs. 5 and 2, respectively, is the potential improvement in the network performance when adopting shorter headway settings, i.e., 0.8 sec and the range headway setting, with Shladover's model. This is due to the faster response of Shladover's model compared to IDM resulting in a stricter materialization of the desired headways in addition

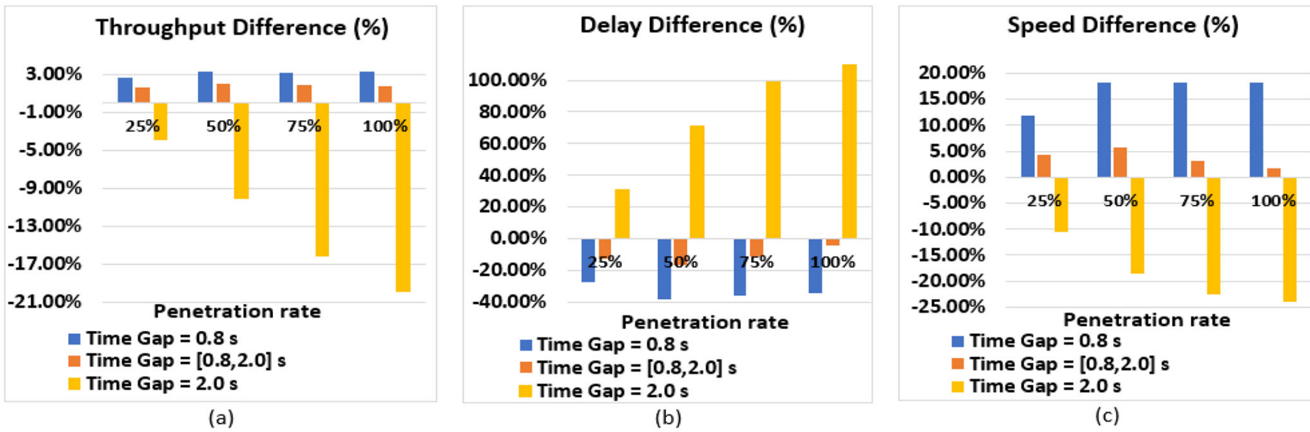

FIGURE 5. (a) Average throughput (b) Average delay and (c) Average speed differences compared to the base case for Shladover-based ACC systems.

to offering a better chance to reap the anticipated benefits from the implementation of headway control strategies [24].

It is also worth mentioning that the network improvements achieved when adopting the short and the range headways taper off and sometimes even slow down at high penetration rates. This is mainly attributed to the ACC vehicles being more strictly compliant to the speed limit of the road than the manually driven vehicles. Speed acceptance for manually driven vehicles is set to 1.1 in this study indicating that they can drive at speeds 1.1 times the speed limit, as opposed to ACC vehicles that have a speed acceptance of 1.0. This may explain the slightly higher improvements achieved in throughput, delay and speed of ACC vehicles with a headway range at 50% penetration as opposed to 100% penetration. This was similarly reported by the authors in [31] concluding their study by the observation that AVs appear to provide more benefits in congested situations than in free flow situations as a result of lower speed acceptance.

Speed Profiles (Space mean speed Vs Time mean speed): Commonly in the literature, testing the impact of ACC is often performed on short road sections. In this work, we argue that there is value in examining the impacts of ACC on a long freeway where bottleneck dynamics can be observed. Therefore, in addition to the average performance results, we examine the spatiotemporal profile of congestion, i.e., where the bottlenecks are, how they form and dissipate over space and time which is crucial to complete the quantification of the impacts of automation and determine the necessary control. Average speeds (calculated every 15 minutes) at each detector location along the freeway stretch are collected and plotted as speed profiles for the entire simulation period. Figs. 6a, 6b, 6c and 6d show a map of the QEW freeway outlining the flow direction and the corresponding speed profiles the for the worst-case scenario, i.e., ACC users adopting a 2.0 sec headway, the more realistic scenario, i.e., ACC users choosing from a range of admissible headways, and the best-case scenario, i.e., ACC users adopting the minimum 0.8 sec headway, respectively.

In the base case speed profile, there are two major congestion areas: one in the west, and one to the east which both last for almost the whole length of the simulation. It can be observed from Fig. 6b where ACC users adopt a 2.0 sec headway that the speed profile deteriorates even with the smallest introduction of ACC vehicles and the deterioration increases further as the penetration rate increases with the eastern and western congestion spots propagating further upstream. However, as the vehicle population becomes more homogenous, i.e., almost all vehicles are ACC-equipped, the network performance does not deteriorate further. Fig. 6c shows the speed profiles of the QEW freeway stretch for the ACC-equipped vehicles with the randomly-distributed headway setting [0.8, 2.0], which is considered a more realistic scenario as it captures the different driving styles and behavior of ACC system users. Speed improvements are observed with this headway setting and as the percentage of ACC vehicles increases improvements increase further such that partial dissipation of the two western and eastern congestion hotspots has been observed at 100% penetration of ACC vehicles. The 0.8 sec speed profiles illustrated in Fig. 6d show the highest improvement in speeds compared to the range and the long headway scenarios and such improvements are found to increase with the penetration rate in line with the range headway speed profiles shown in Fig. 6c.

Note that all previous performance metrics are network-wide metrics, hence, the average network speed results in Fig. 5c is calculated using the mean journey speed for each vehicle which is a representation of the space mean speed. On the other hand, we generate the speed profiles using detectors data across the freeway which measure the average speed of vehicles that have crossed the detector within a time interval and is a representation of the time mean speed. It is known that the time mean speed is always higher than the space mean speed and it has been found in [32] that the differences between the two speed becomes more significant in low-speed regions, i.e., congested conditions, which explains the different deterioration/improvement numbers observed in both Fig. 5c and Fig. 6.

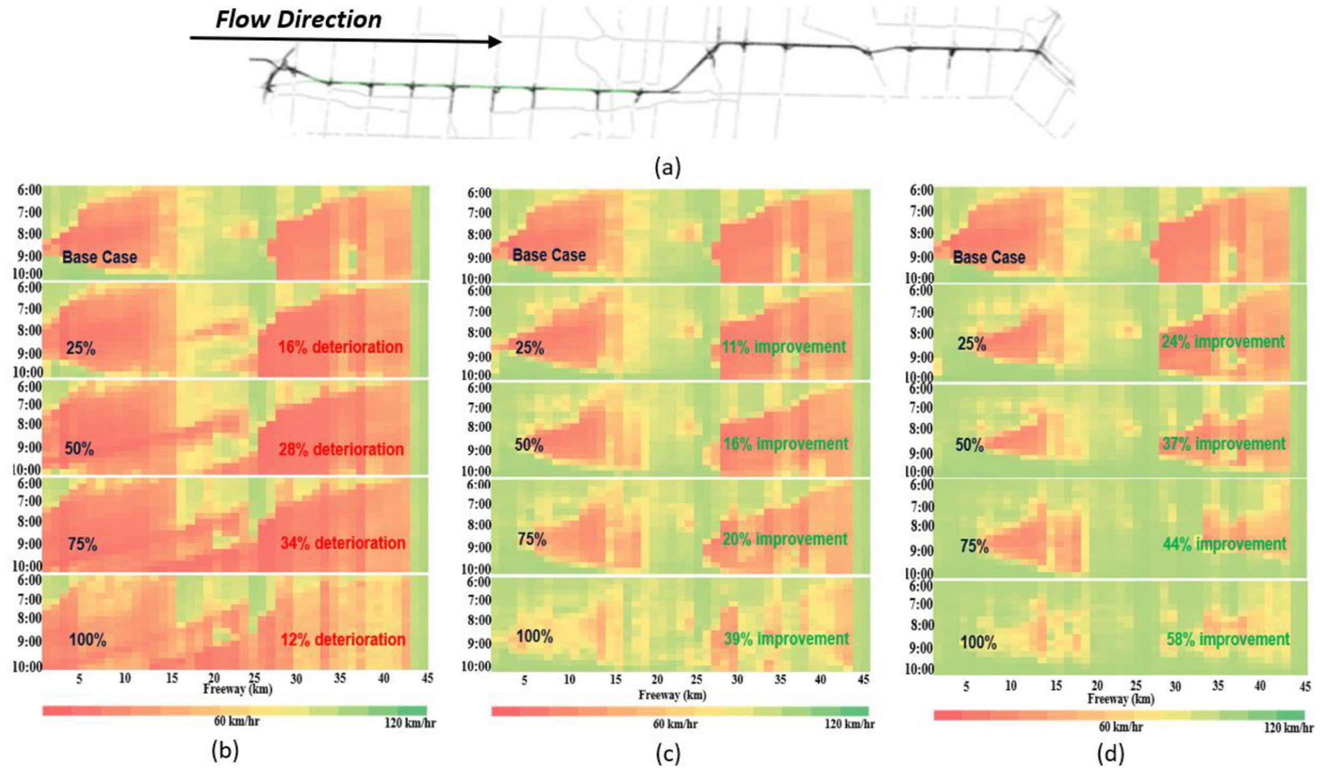

FIGURE 6. Speed Profiles on (a) QEW freeway for Shladover-based ACC when ACC users adopt (b) 2.0 sec headway, (c) a random headway between [0.8, 2.0] sec, and (d) 0.8 sec headway.

V. CONTROLLED ACC

Based on the ACC quantification results above as well as in the published literature, ACC systems have the potential to improve the transportation network performance. However, if conservative values are set for their parameters, then the ACC systems may lead to a deterioration in the transportation network performance. For example, most ACC-equipped vehicles offer a desired headway range from around 0.8 to 2.0 s with the recommended desired time headway set to 2.0 s. Moreover, some drivers may prefer to choose more conservative headways than those employed in manual driving for safety concerns. Such headway settings would lead to a significant reduction of the freeway performance as shown earlier. This can be mitigated if the settings of the ACC vehicles can be updated dynamically in real time according to the traffic state through the operation of an ACC-based control strategy. ACC control strategies can be implemented to reduce the deteriorations caused by adopting conservative system settings as well as increase the improvements by exploiting the full capabilities of such systems. For example, the authors in [33] study the optimization of ACC system parameters, however, this study is based on an off-line optimization technique which does not cope well with the dynamically changing traffic conditions. There are a few studies that address this limitation by adjusting the ACC system settings adaptively in real time according to dynamic traffic conditions such as in [27], [29], and [34].

A. ACC CONTROL STRATEGY

After quantifying the impacts of ACC systems on one of Ontario's busiest freeways, the focus here is to examine the effect of a simple ACC-based control strategy which aims to adjust in real time the ACC settings of equipped and connected vehicles, in particular the headway parameter, based on the prevailing traffic conditions. The main philosophy behind the proposed concept is to: (i) leave the ACC-settings untouched at their driver-selected values if the traffic flow is under-critical to limit interventions only to situations that call for efficiency increase; and (ii) change the ACC-settings to improve the network performance when critical traffic states are imminent which is dependent on real-time information about the current traffic conditions. The proposed strategy considers that the ACC-equipped vehicles communicate with a traffic management center which suggests to the drivers or imposes directly appropriate values for the time headway parameter. The strategy requires real-time flow and speed measurements for freeway sections, as a basis for the issued ACC-settings recommendations in each section.

Our proposed control strategy is a simple on-off strategy inspired by but simpler than the control strategy implemented in [27] and [29] which calculates the suggested time headway as a decreasing function of the current section flow such that the maximum headway, T_{max}, is suggested when the traffic flow is low, and as the flow increases the suggested headway decreases, till it reaches the minimum headway T_{min} when the section flow is equal to a certain threshold

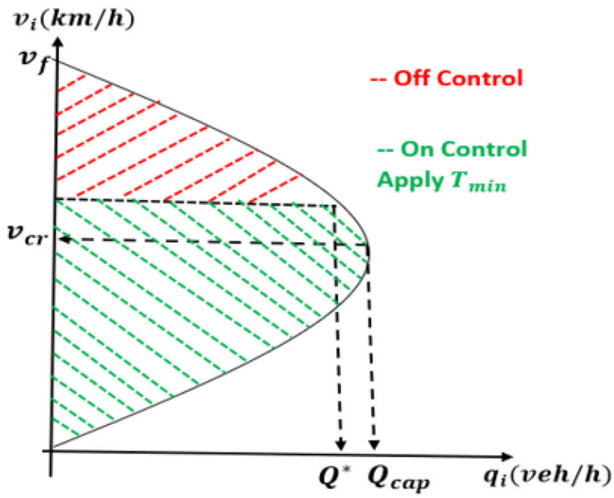

FIGURE 7. Proposed ACC Control Strategy.

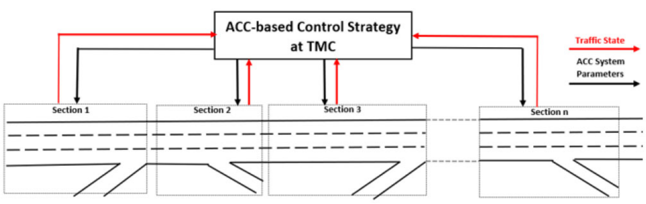

FIGURE 8. Proposed ACC Control Strategy.

which should be lower than the capacity, so that the headway is reduced to the minimum value before the flow reaches the nominal capacity of the section. Our proposed control strategy aims for fewer interventions by imposing the minimum headway T_{min} only in critical or near critical traffic states and leaves the headway to the default user-selected values otherwise. The imposed control strategy is shown in Fig. 7 and outlined in equation (12) which shows that the minimum headway is applied: (1) in congested traffic conditions, i.e., $v_i < v_{cr}$ where v_{cr} is the critical speed, or (2) when approaching the section capacity, i.e., $q_i > Q^*$, where Q^* is just below the section capacity, while it leaves the default settings set by the user in otherwise situations, hence we refer to it as the On-Off control strategy. Our freeway is divided into sections and the infrastructure-based control strategy is applied via a traffic management center at every section independently, as illustrated in Fig. 8.

$$T_{applied,i} = \begin{cases} T_{min} & if\ \ v_i < v_{cr} \\ T_{min} & if\ \ q_i > Q^* \\ T_{default} & else. \end{cases} \tag{12}$$

B. ACC CONTROL NETWORK-WIDE PERFORMANCE RESULTS

We implement the On-Off Control strategy for the 2.0 sec desired headway scenario where huge deteriorations were observed in the uncontrolled ACC case aiming at reducing them with control. We also implement control for the [0.8, 2.0] desired headway scenario, being one of the possible headway scenarios adopted by ACC users, aiming at increasing the improvements achieved and preventing any bottlenecks from being activated. The control strategy is updated every $T_c = 5$ mins, receiving real-time measurements of flow and speed for every section of the freeway.

ACC-Equipped Vehicles With Long Desired Headways: Significant deteriorations have been observed when the desired headway used is equal to 2.0 sec which corresponds to the ACC users abiding by the default recommended headway settings and representing a worst-case scenario in which control is deemed more essential to reduce the magnitude of such deteriorations. Average throughput, delay and speed differences compared to the base case with and without control are presented in Fig. 9. With ACC control it is observed that throughput, delay, and speed deteriorations without control turned to improvements with control with the magnitude of improvements increasing as the penetration rate increases. It is worth mentioning that improvements were achieved despite the huge deteriorations observed without control for this desired headway setting, i.e., average throughput, delay and speed deteriorated by around 20%, 110% and 24%, respectively, at 100% penetration of ACC-equipped vehicles without control which then turned to improvements by applying control since they improved by 2%, 15% and 12%, respectively, compared to the base case. This emphasizes the importance of ACC control especially in the early adoption stage of such systems when users are more likely to go with manufacturers recommendations for safety and comfort concerns.

ACC-Equipped Vehicles With a Desired Headway Range: For the case when the headway ranges between the minimum and maximum values offered by ACC system manufacturers, i.e., 0.8 sec to 2.0 sec used in this work, no deteriorations were observed, and some slight improvements were even possible without control. In this scenario, we wanted to investigate the effect of control aiming at achieving more improvements by fully exploiting the capabilities of ACC systems and preventing traffic breakdown to the extent possible through headway control. Throughput, delay, and speed differences compared to the base case with and without control for this headway setting are presented in Fig. 10. It is observed that throughput, delay, and speed improvements without control are further improved by applying control with the magnitude of improvements increasing as the penetration rate increases. For example, average throughput, delay, and speed improved by around 2%, 4% and 2% respectively, at 100% penetration of ACC-equipped vehicles without control which is further improved by applying control to 3%, 28%, 17% respectively, compared to the base case. Despite achieving improvements without control for this headway setting, ACC control here will allow the maximization of these improvements by fully utilizing the available road capacities in critical and near critical traffic situations aiming at preventing traffic breakdown to the extent possible.

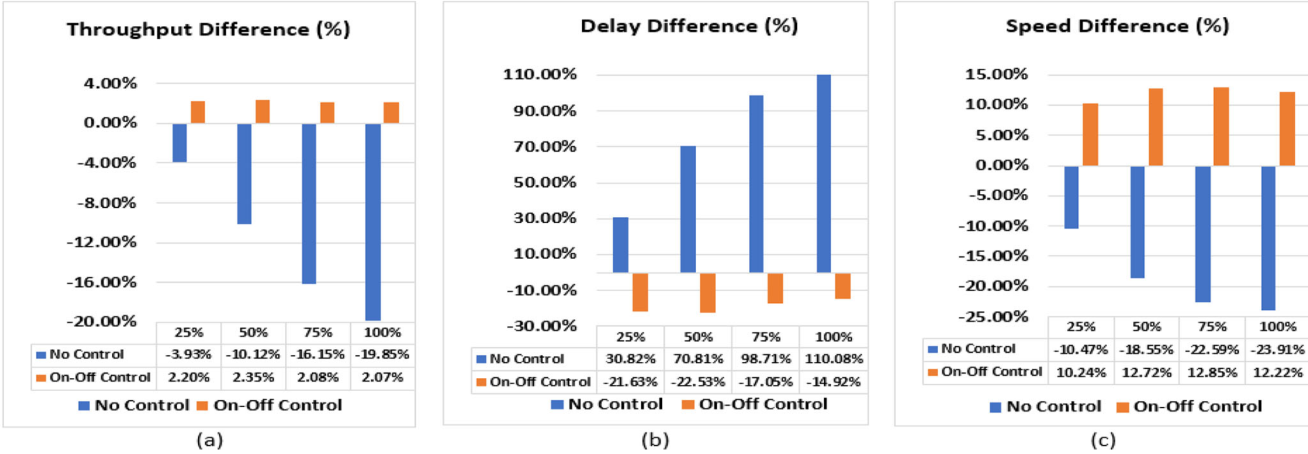

FIGURE 9. (a) Average throughput (b) Average delay and (c) Average speed differences compared to the base case before and after control for Shladover-based ACC systems when ACC users adopt a 2.0 sec headway.

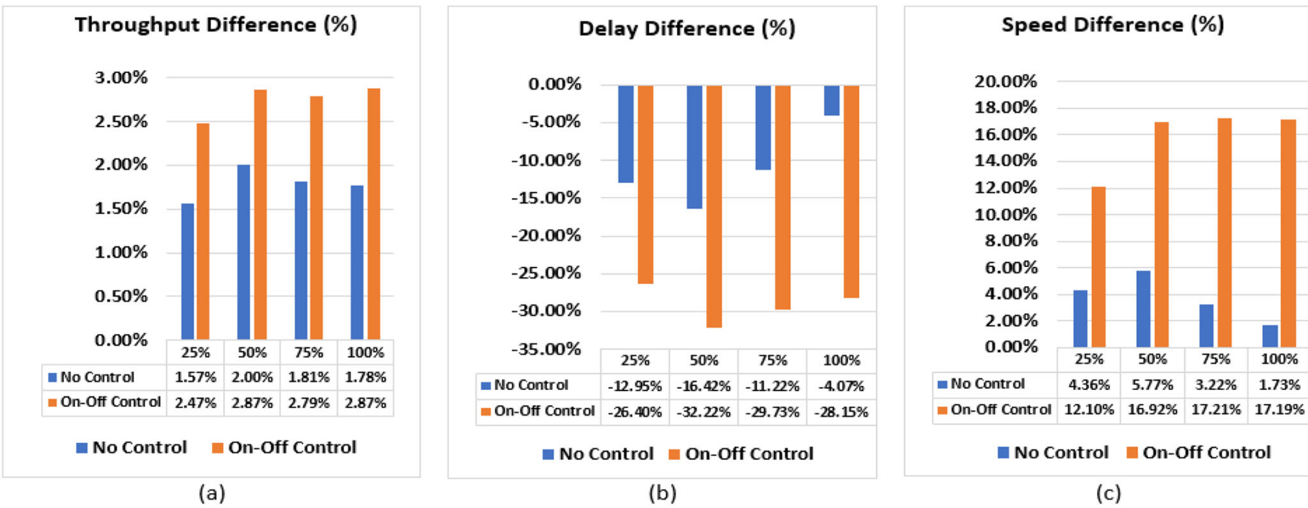

FIGURE 10. (a) Average throughput (b) Average delay and (c) Average speed differences compared to the base case before and after control for Shladover-based ACC systems when ACC users adopt different headways ranging between [0.8, 2.0] sec.

Speed Profiles of the QEW: Fig. 11a shows the speed profiles of the QEW freeway stretch for the ACC-equipped vehicles with the long-desired headway setting when ACC control is applied. By applying headway control we notice that speed deteriorations observed without control shown previously in the speed profiles in Fig. 6b turned to improvements which increase as the penetration rate increases. Such improvements result in partial dissipation of the two western and eastern congestion hotspots at high penetration rates. Fig. 11b shows the speed profiles of the QEW freeway stretch for the ACC-equipped vehicles with the randomly distributed headway setting between [0.8, 2.0] sec when applying ACC control. It can be observed that the speed improvements achieved with this headway setting without control shown in Fig. 6c further increase by applying headway control. Applying ACC control resulted in partial dissipation of the two western and eastern congestion hotspots at low penetration rates and full dissipation at moderate to high penetration rates as observed in Fig. 11b as opposed to Fig. 11a where partial dissipation of congestion hotspots was noticed only at high penetration rates due to the initially adopted longer headways.

This emphasizes the need to implement ACC control to reduce the deteriorations caused if users adopt conservative ACC system parameters in addition to preventing traffic breakdowns resulting in an overall improvement in the network performance. It is worth mentioning that the improvements achieved with the 0.8 sec headway presented in Fig. 6d seem to be lower than the improvements achieved with the controlled 2.0 sec and range headway scenarios shown in Fig. 11a and 11b, respectively. The reason for that is the lesser number of vehicles that were waiting outside the network with the 0.8 sec headway setting compared to the other headway settings in the controlled and uncontrolled scenarios thereby more vehicles were being served with the 0.8 sec headway. Moreover, the number of vehicles

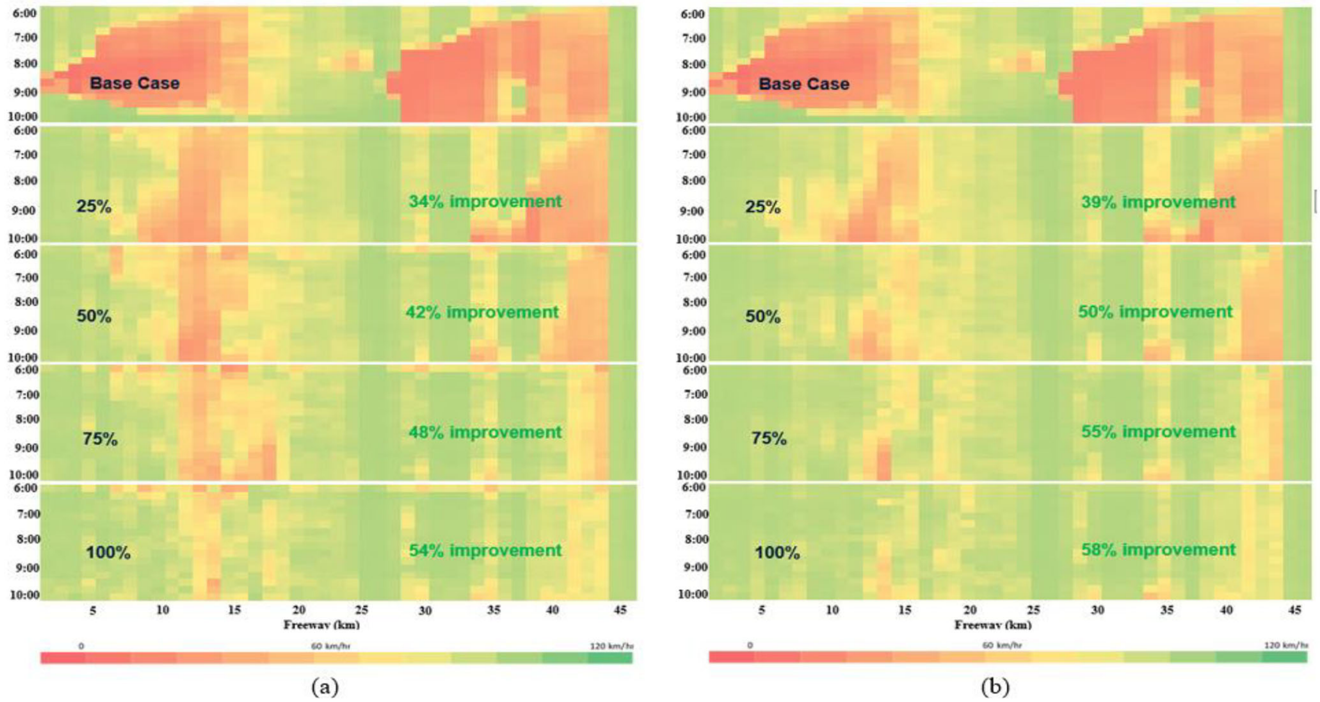

FIGURE 11. Speed Profiles on QEW freeway for Shladover-based ACC after applying headway control when ACC users adopt (a) 2.0 sec headway and (b) a random headway between [0.8, 2.0] sec.

waiting to enter didn't change between the controlled and uncontrolled range and 2.0 sec headway scenarios, hence the improvement achieved is only contributable to the control strategy applied. Note that there were vehicles waiting to enter in the base case (Gipps scenario), those vehicles decreased with the range headway and decreased further with the 0.8 sec headway but increased with the 2.0 sec headway. Even though the ACC scenario with the range headway setting served more vehicles than the Gipps scenario (human-driven) tangible improvements were achievable. On the other hand, the ACC scenario with the 2.0 sec headway setting served less vehicles than the Gipps scenario, and the deteriorations were significant. While, with the 0.8 sec headway setting most of the vehicles were being served and improvements were significant.

VI. KEY FINDINGS AND RECOMMENDATIONS

Based on the research presented in this paper, we provide the following key findings and recommendations:

a) *The IDM model produces a smooth ACC car following behavior, but with a slow response leading to headway errors:* It has been reported in the literature according to the experimental field studies in [23], [24], using a few ACC cars in an uncongested regime, that the IDM has a delay in responding to the speed changes by the leading car. This was confirmed in our simulations as well. The troubling behavior of the IDM is mainly reflected in the headway error which is the difference between the achieved headway and the desired headway. This headway error will result in an inaccurate quantification of the impact of such systems in addition to the inability to fully exploit the benefits from implementing headway control strategies since the short headways will not be strictly imposed.

b) *Our ACC quantification results act as a first approximation of the impact of such systems on the congested transportation network:* The exact representation of the complex real driving process by a car following equation is a challenging task, and different models have been adopted in the simulation investigations of the ACC-related studies in the literature. Therefore, we picked the two most widely used ACC car following models in the literature, i.e., the IDM and Shladover's model, and we moved forward with Shladover's model since it was found to have a faster response and a lower headway error [24], hence a better representation of ACC systems and a more accurate quantification of their impacts on the transportation network performance.

c) *The common default time headway setting of 2.0 seconds causes performance degradation while shorter time headway settings improve performance:* The results of this study provide evidence that if the time headway of ACC vehicles is to be left to its default recommended value of 2.0 seconds, the freeway performance will deteriorate. As the percentage of ACC vehicles with a 2.0 sec headway increases such deteriorations were found to increase as well. On the other hand, the results of the 0.8 sec and

[0.8, 2.0] sec headway settings show an improvement in performance, and the improvements increase as the penetration rate of ACC vehicle increases.

d) ACC Control had a significant effect on performance: The result of implementing ACC control that varies the time headway according to the traffic situation has been proven as a promising solution to enhance the performance of ACC systems. Implementing this headway control strategy has been found to turn deteriorations to improvements when long headways are adopted by users or further increase the improvements when users select their desired headways from the range of the admissible headways.

e) Aiming for fewer interventions with ACC Control: Our proposed On-Off control strategy imposes the minimum headway only when needed, i.e., in critical and near critical traffic situations, first to maximize the road capacities and avoid traffic breakdown. The reason for limiting interventions to when needed is for safety concerns such that the minimum 0.8 sec headway is not imposed for the whole speed range but rather when the speed is around or less than the congestion speed, i.e., in our case $v_{cr} = 50\ km/hr$, which is considered a reasonably low speed at which small headways can be imposed without jeopardizing safety. It has also been reported in the literature [35] that there should be a threshold time headway setting above which an ACC car platoon can be string stable and below which the platoon can be string unstable which is subject to further research. In our future work we aim to explicitly take the safety and stability into consideration and quantitatively investigate the impact of short headways on surrogate safety measures such as time to collision as well as on string stability.

VII. SUMMARY AND CONCLUSION

The first target of this study is to quantify the potential effects of ACC, being one of the most mature and widely spreading systems in today's cars. The effects of ACC systems are investigated on the performance of a congested freeway stretch in Ontario, Canada. The assessment was conducted in Aimsun, in which a model of a 45-kilometer stretch of the QEW was constructed and calibrated for the morning peak period. The car following models adopted to represent the behavior of ACC in this study were the IDM model and Shladover's model and we moved forward with the latter, first, to overcome the IDM headway error drawback observed in our simulations and reported in the literature, and second, since Shladover's model was formulated based on field experiments and was proven to have a faster response than IDM. The network performance was assessed under different time headway settings and varying market penetration rates. The results show that the desired time headway setting has a direct impact on the network performance, the smaller the time headway setting is, the greater the improvements become. While adopting long headways lead to performance deterioration which gets worse with the penetration rate increase. Therefore, if auto manufacturers recommend long time headways, for comfort and convenience reasons, and users abide by such default settings, then the performance will significantly deteriorate. This highlights the need for implementing proper control strategies that could guide road authorities for the optimal usage of ACC systems, with regards to traffic management.

Consequently, the second target of this study is to investigate the effect of ACC control on enhancing the system performance. For this, we proposed a simple on-off ACC-based traffic control strategy by imposing the minimum headway in critical and near critical traffic situations which was found to improve the freeway traffic performance significantly. The improvements resulting from adopting a headway ranging between the minimum and maximum admissible headways were found to further increase with ACC control. Moreover, the significant deteriorations caused by adopting the recommended conservative headway settings, turned to improvements by implementing the proposed control strategy which emphasizes the importance of ACC control especially in the early adoption stages when we are not certain about how users will adopt such systems and what will be their exact effect on the traffic performance. Lastly, it is important to note that ACC systems may vary considerably from one manufacturer to the other and they are mostly proprietary. It is also anticipated that ACC controllers may change in the coming years as auto manufacturers improve their systems to act faster especially in relation to the desired following distances. However, it is not the scope of this paper to produce better ACC systems or address the intricate details of such systems, but rather to demonstrate their impact of urban traffic based on a generally accepted and utilized car following model reproducing the basic car following behavior. Our results do provide useful quantitative insights which could be considered as a first good approximation to understand the effect of ACC systems on congested traffic environments.

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