Multi-Objectives Optimization Controller for Cooperative Adaptive Cruise Control

Zijia Zhong
Graduate Research Assistant
John A. Reif Jr. Department of Civil and Environmental Engineering
New Jersey Institute of Technology
17 Summit Street, Newark, NJ 07102
Telephone: (973)596-8497
zz46@njit.edu

Joyoung Lee, Ph.D.
Assistant Professor
John A. Reif Jr. Department of Civil and Environmental Engineering
New Jersey Institute of Technology
17 Summit Street, Newark, NJ 07102
Telephone: (973)596-2475
jo.y.lee@njit.edu

And
Liuhui Zhao
Graduate Research Assistant
John A. Reif Jr. Department of Civil and Environmental Engineering
New Jersey Institute of Technology
17 Summit Street, Newark, NJ 07102
Telephone: (973)596-6086

Corresponding Author: Joyoung Lee
Word Count: 6,950 (5,200 Words + 7 x 250 Figures and Tables)

ABSTRACT

Automated longitudinal control (ALC) technology has gained increasing attention due to its promising capability in creating safer, more efficient, and more comfortable vehicle operations on highway. ALC has been tested through Cooperative Adaptive Cruise Control (CACC). By forming a vehicular platoon with a short intra-platoon vehicular headway (e.g. 0.9 seconds), CACC is envisioned to drastically improve highway mobility while maintaining string stability under traffic disturbances. Several research efforts have been performed to handle ALC for CACC either without optimization process or with pseudo-multi-objective optimization process. This paper proposes a multi-objective optimization (MOOP)-based ALC framework for CACC by taking into consideration four optimization objectives: mobility, safety, driving comfort, and fuel consumption. As simulation results indicated, the proposed CACC controller achieved the best performance with 0.9- and 0.6- second target headway. Compared to a non-optimization-based CACC controller, the MOOP-CACC achieves 98%, 93%, 42%, and 33% reductions of headway deviation, unsafe condition, jitter rate, and instantaneous fuel consumption, respectively. Lastly, Compared to single-objective optimization (SOOP)-based CACC controller, it appeared that the MOOP-based controller keeps a good balance among all the objectives and hence produce better Pareto-optimality for the entire platoon.

INTRODUCTION

According to the 2012 Urban Mobility Report , the congestion of roadways in the United Sates had caused significant negative impacts (approximately 5.5-billion extra hours, 2.9-billion gallons of wasted fuel, and 56-billion pounds of additional carbon dioxide) *(1)*. All of these negative impacts had added up to a $121-US-Doller bill in 2011. Necessary steps making the surface transportation smarter, safer, and greener need to be taken. It is believed that a more efficient surface transportation system could be achieved via connected vehicle (CV) technologies, owning to the rapid advancement of information and communication technologies (ICT). CV Technologies have gained increasing amount of traction for their promising capability to drastically enhance the performance of our transportation system. The Intelligent Transportation Systems Joint Program Office (ITSJPO) in the US Department of Transportation (USDOT) has initiated the 6-year CV Pilot Deployment Project in 2013*(2)*. And recently, USDOT has established two primary strategic priorities: realizing connected vehicle implementation and advancing automation *(3)*.

Among the applications of advanced driver assistance system (ADAS), adaptive cruise control (ACC) system has been extensively studied. Typically, ACC employs a proportional derivative controller, which controls the acceleration of a following vehicle based on the bumper-to-bumper gap and relative speed with respect to the preceding vehicle *(4)*. Lidar or other sensing technologies are adopted to obtain the necessary data. Powered by Dedicated Short Range Radio (DSRC), two-way vehicle-to-infrastructure (V2I) or vehicle-to-vehicle (V2V) wireless communication is available for transmitting instantaneous vehicular information (e.g. speed, headway, and acceleration) under CV environment. Hence, cooperative Adaptive Cruise Control (CACC) can be considered as an evolution of commercially available ACC with an additional layer of connectivity. By forming a cooperative vehicular platoon with a short intra-platoon headway (e.g. 0.9 seconds), CACC is promising in drastically improved highway mobility.

As CACC technology becoming more mature, a system wide optimal controlling scheme for CACC platooning is crucial in ensuring the full use of the technology: a realistic and practical controller should not only consider major aspects (e.g. mobility performance, safety performance, and environmental impact etc.) of vehicular longitudinal control in a dynamic traffic context, but it also should be generic such that a large variety of objectives could be seamlessly incorporated. Non-optimization *(5)* or pseudo-multi-objective optimization *(6)*-*(7)* is somehow inadequate in providing such generality as well as flexibility. To tackle this issue, this paper proposes a Genetic Algorithm- and multi-objective-optimization-based CACC (MOOP-CACC) controller, which is able to adopt wide range of objectives and find multiple trade-off optimal solutions utilizing vehicular information disseminated under CV environment.

The remainder of this paper is organized as follow. In the next section, the literature review summarizes the current state-of-the-art research in vehicle longitudinal control and identifies the research gap for CACC. The methodology section goes into details in the proposed vehicle control algorithm, followed by a numerical example and simulation study in the next section. Concluding remarks and future research are offered in the last section.

LITERATURE REVIEW

Vehicle Longitudinal Control

Vehicle control can be classified into two broad categories: lateral control and longitudinal control. The main objective of vehicle lateral control is to keep the vehicle on the desired trajectory, usually in the center of the lane, from wind gust disturbance, road surface condition or even unintentional lane-drifting by human driver. In the event of CACC, however, the primary objective is longitudinal control. Van Arem et al.*(8)* proposed a meta-model, named Sustainable Mobility Methodologies for Intelligent Transport Systems-Integrated Full-Range Speed Assistant (SUMMIT-IRSA), which supported the development of ADAS in terms of assessment of technical functionality. Three ADAS models were derived from the meta-model: 1) an ACC controller, 2) a time headway CACC controller, and 3) average speed CACC controller. In the first CACC controller, the acceleration rate was determined by the minimum acceleration rates of the preceding vehicles. In the second controller, the acceleration rate of a controlled vehicle was determined by both minimum acceleration rates of all the preceding vehicles and an error feedback of the average velocity. Safety, string stability, and comfort measure were employed to evaluate the performance of these algorithms.

Yu and Shi *(9)* proposed an improved cooperative car-following model by taking into consideration of multiple instantaneous vehicular gaps and the historical gaps with memory. The memory in this study referred to a variable in traffic hysteresis theory *(10)* for the motion of a vehicle after sufficient time steps. In essence, the model determined the position of each vehicle at any time interval by considering all the vehicular gaps in a platoon as well as speed information. Four different combinations of the weight coefficients of two preceding vehicles were proposed. Based on the numerical examples, the authors concluded that the traffic flow becomes most stable and safe when taking into account the change of multiple vehicular gaps (e.g. 3 preceding vehicular gaps) with memory step of two.

Wang et al. *(6)-(7)*proposed a rolling horizon control framework, under which different control objects were optimized, considering the predictive behaviors of other vehicles. An enhanced predictive ACC controller with an explicit safety mechanism and a fuel consumption objective were proposed. To improve the control framework for cooperative systems, the authors also proposed two multi-anticipative controllers (MACC) *(7)*: 1)CACC-MP (i.e., perfect knowledge of human follower simulated by Hally's *(11)* car following model) and 2)CACC-MI (imperfect knowledge of the human follower by incorporating Intelligent Driver Model *(12)*). Experimental scenarios were designed to examine the performance of MACC and CACC in terms of reactions to the disturbance, oscillation of gap, speed and acceleration. The authors reported that the cooperation between equipped vehicles and human drivers could dampen traffic disturbances in acceleration and increase queue discharging rate.

Li et al. *(13)* had extended the intelligent driver model *(12)* by incorporating the power cooperation of the immediate preceding vehicle. Linear stability analysis showed that the consideration of power output of a receding vehicle can improve the traffic flow stability. Montanaro et al. *(14)* put forward an extended CACC controller, under which the communication was asymmetrical, rather than symmetric-bidirectional communication. The objective of the algorithm was to make the controlled vehicle attain the velocity of the leading vehicle and pre-determined gap. Ge and Orosz*(15)* performed a vehicle dynamic with delayed acceleration feedback of a CACC platoon system.

Lee et al. *(5)* conducted an evaluation of the impact of CACC on the mobility and safety of traffic flow, using a VISSIM simulation test bed and Safety Surrogate Assessment Model (SSAM). Compared to most of aforementioned study, Lee's study focused on assessing the potential benefits for both mobility and safety under a wide range of traffic scenarios. To tackle the CACC vehicles operating under mixed traffic environment, a CACC algorithm which included rear-, front-, and cut-in join was proposed. Among all the scenarios tested, the authors reached the conclusion that at a market penetration rate of 30%, the promising mobility benefits of CACC was shown and that 0.9-second headway was better than 0.6-second headway, according to the time to collision and post encroachment time in the SSAM. Arnaout and Bowling *(16)* constructed a simulation test bed to evaluate three different CACC deployment strategies: 1) no CACC vehicle as default, 2) CACC vehicles scattered on all the lanes, and 3) CACC vehicles with priority access to HOV lane in mixed traffic. The authors concluded that great potential benefit of CACC could be realized by placing CACC vehicle on HOV lanes, when the market penetration is below 40%; the benefit of CACC could be realized even in the absence of CACC-HOV dedicated lanes, when the MP is above 40%.

CACC Implementation

The Safe Road Trains for the Environment (SARTRE)*(17)*, funded by European Union, had developed a solution which allowed a platoon of vehicle led by a trucks driven by a professional driver. The following vehicles, under autonomous vehicular control, freed the passengers for doing non-driving related tasks. Without the necessary change of existing roadway infrastructure, the concept was successfully demonstrated on a conventional highways in a mixed traffic environment. In the United States, the PATH program integrated the V2V communication capability to ACC system and conduct an experiment of longitudinal motion control of eight vehicles on a closed highway segment*(18)*. Bu et al. *(19)* had proposed a generic process of formulating a real-world application with multiple constraints in the control problem. Then they modified a commercially available ACC system on Infinity FX45 vehicles and had the cars retrofitted with the CACC system designed by the California PATH program. The field test of the CACC algorithm reported that CACC equipped vehicles could operate at time gaps between 0.6 seconds and 1.1 seconds, compared to ACC which operates at a time gap between 1.1 to 2.2 seconds.

Omae at al. *(20)* proposed an inter-vehicle control scheme for implementing CACC-enabled heavy trucks. The contents and format of the V2V message being transmitted was summarized. Four slightly different CACC control algorithms tailored to different vehicle types (e.g. electric light vehicles, general passenger car, and heavy-duty vehicle) were proposed. A field experiment constituted by 4 heavy trucks equipped with the proposed algorithms was carried out. The focus of the field experiment was how the vehicles, based on the CACC controller, form and exit the platoon; and when the control mode was switched among CACC, ACC, and Manual mode in the event of communication failure. The experiment proved that the CACC controller successfully overcame communication failure by switching to proper control mode.

Milares et al. *(21)* conducted a field experimentation of CACC using commercially available vehicles which were retrofitted V2V communication capability. With the incorporation of the gap regulation and gap closing controller, three tests: 1) gap setting change test, 2)cut-in and cut-out test, and 3) a comparison test between manufacture install ACC and augmented CACC were carried out. Based on the success of the field experiment, the authors re-emphasized that the knowledge of information about the preceding vehicles was significant in improving string stability. Similar CACC field implementations can also be found in *(22-26)*.

Multi-Objective Optimization

Optimization is the selection of a best element regarding criteria from a set of alternatives. In multi-objective optimization (MOOP), more than one, typically conflicting, objective functions are optimized simultaneously. The output of a MOOP is a Pareto frontier which is consisted of multiple equally good solutions, if no additional subjective preference information is provided. MOOP method has been proposed to deal with complicated optimization problems in transportation engineering. Wu et al. *(27)* reviewed the applications of multi-objective optimization techniques in highway asset management and concluded that MOOP could be effective in supporting business processes of infrastructure management. A multi-objective binary nonlinear programming model was proposed by Wu et al. *(28)* to prioritize the transit stops improvement for American Disability Association (ADA) compliance. An ideal fair ramp metering problem was formulated by Meng and Khoo *(29)*. In their study, the Pareto-optimality was explored using Non-dominated Sorting Genetic Algorithm under dynamic traffic flow pattern. Both system efficiency and equity issue were addressed by Meng's MOOP. Abdelgawad et al. *(30)* proposed optimal evacuation strategies using mass transit by solving the MOOP with Genetic Algorithm.

The majority of reported MOOP methods linearly transformed the multi-objective optimization problem into single objective optimization (SOOP) by using some user defined parameters (i.e., weight factors) for simplifications, resulting in a multi-objective linear programming (practically a SOOP). As Das *(31)* pointed out, in a preference-based (e.g. with assigned weighted factors) MOOP, a change of the preference vector does not necessarily result in a change among trade-off optimal solutions, meaning the other optimal solutions could be potentially overlooked despite change of preference vector. However, the majority of real-world MOOP problems in their nature require obtaining as many trade-off solutions as possible, before making selection based upon higher-level information. Genetic Algorithm (GA) is suitable to achieve this goal*(32)*. GA mimics the nature of evolution principle resulting in a stochastic search for fittest (optimal) solutions. GA can capture multiple optimal solutions more efficiently, because a population of solutions, instead of one, are updated in each iteration. In a MOOP context, it is paramount to find a set of solutions sparing as far as possible in the Pareto frontier before selecting one based on high-level information.

In summary, despite the appealing advantages of CACC, only a limited field tests have been conducted due to various reasons (e.g. ITS infrastructure availability, administrative concerns) of current state-of-the-practice of CACC. Hence, testing and evaluating CACC controller are typically performed by simulation. Secondly, very few research had truly explored the Pareto-optimality, if optimization technique was employed at all, in multi-objective optimization for designing CACC controllers. Therefore, this study aims to develop a multi-objective-optimization-based CACC (MOOP-CACC) and to conduct the proof-of-concept test on an integrated simulation test bed.

METHODOLOGY

Platoon-based Optimization Algorithm

Target Headway Deviation

One of the appealing benefits of CACC is its cooperative nature. How quickly CACC vehicles form a platoon and how much deviation each vehicle has from targeted headway is crucial. As well, how swiftly a platoon adjusts and stabilize when additional vehicle is added into the platoon is of importance. Therefore we proposed a target headway deviation objective which represents the time difference between current headway and target headway. This objective only considers the absolute deviation of the targeting headway, which means either positive or negative value of deviation is the same. The safety issue regarding the positive value will be addressed in the subsequent objective function. The objective function of targeted headway deviation to be minimized can be expressed as Eq. 1.

$$\sum_{i=1}^{n} \left| H - h_i(\mathrm{t}+1) \right| \tag{1}$$

where

H-the target headway for the entire platoon, s

$h_i(t+1)$-the instantaneous headway of vehicle i at time interval t+1, s

n-total number of vehicles within a platoon

According to the equation of motion, for the headway of vehicle i at time interval (t+1) is expressed as Eq. (2)

$$h_i(\mathrm{t}+1) = \frac{x_i\,(t) + \left[v_{i-1}(t) - v_i(t)\right]\triangle\mathrm{t} + \dfrac{1}{2}\left[u_{i-1}(t+1) - u_i(t+1)\right]\triangle\mathrm{t}^2}{v_i(t) + u_i(t+1)\triangle\mathrm{t}} \tag{2}$$

where

Δt- updating interval for the controller, s
$x_i(t)$- bumper-to-bumper gap of vehicle i to immediate preceding vehicle in time interval t, m
$v_i(t)$-instantaneous speed for vehicle i at time interval t, m/s
$v_{i-1}(t)$-instantaneous speed for vehicle i-1 at time interval t, m/s
$u_i(t+1)$-instantaneous acceleration for vehicle i at time interval t, m/s^2
$u_{i-1}(t+1)$-instantaneous acceleration for vehicle i-1 at time interval t, m/s^2

Therefore the Eq. (1) and Eq. (2) can be combined into Eq. (3)

$$\sum_{i=1}^{n}\left| H-\frac{x_i\,(t)+\left[v_{i-1}(t)-v_i(t)\right]\Delta \mathrm{t}+\frac{1}{2}\left[u_{i-1}(t+1)-u_i(t+1)\right]\Delta \mathrm{t}^2}{v_i(t)+u_i(t+1)\Delta \mathrm{t}} \right| \tag{3}$$

where all variables as previously defined.

Unsafe Condition Objective

Safety is of paramountcy in designing a vehicle controller. Maximization of safety, in other words, also means the minimization of critical or unsafe condition. Wang et al. *(4),(6)* proposed a safety objective where the penalty was assessed exponentially when the vehicle instantaneous gap was smaller than the pre-defined critical distance. For the consistence of the discussion, the objective of unsafe condition is adopted and then minimized. In view of that a sufficiently safe distance also depends on the current speed of a pair of two vehicles, we proposed the use of headway, which already factors in instantaneous speed in our controller instead. With such conversion, the objective function of unsafe condition can be expressed as in Eq. 4.

$$\sum_{i=1}^{n} e^{\frac{h_{i,0}}{h_i\,(t+1)}} \tag{4}$$

where,

$h_{i,0}$-the minimum headway defined by the driver of vehicle i, s
$h_i(t+1)$-the headway for vehicle i at time interval t+1, s

Similarly, Eq. (4) can be converted to Eq. (5) based on Eq. (2)

$$\sum_{i=1}^{n} \mathrm{e}^{\frac{h_{i,0}[v_i\,(t)+u_i\,(t+1)\Delta t]}{x_i\,(t)+\{[v_{i-1}(t)-v_i\,(t)]\Delta t+\frac{1}{2}[u_{i-1}(t+1)-u_i\,(t+1)]\Delta t^2\}}} \tag{5}$$

Vehicular Jitter Objective

Vehicular jitter is defined as the switch between acceleration and deceleration. Besides, the magnitude of change of acceleration should not be overlooked. For instance, even a vehicle does not switch between acceleration and deceleration, drastic change within acceleration or vice versa can result in discomfort riding experience. The discomfort threshold is also a dependent of speed: A 2 m/s^2 deceleration rate yields significant difference between at 120 km/h and at 40km/h. Therefore, a coefficient considering instantaneous vehicle speed was adopted. The vehicular jittering to be minimized can be formulated as Eq. 6.

$$\sum_{i=1}^{n} e^{\beta \frac{|u_i(t+1)-u_i(t)|}{u_{comfort}}} \tag{6}$$

where,

β-adjustment coefficient for instantanteous speed

$u_{comfort}$-the comfortable acceleration threshold, m/s^2

$u_i(t),\ u_i(t),$ as previously defined

Fuel Consumption Objective

The fourth objective to be minimized is fuel consumption. Due to the microscopic nature of CACC controllers, an operational-level emission model is desired. Rakha et al. *(33)* proposed a microscopic emission model which is capable of estimating accumulated environmental impacts (e.g. fuel consumption, carbon dioxide) for individual vehicle. Instantaneous vehicular speed and acceleration rate data is used for the models which yield second-by-second resolution estimation, as shown in Eq. 7.

$$\begin{cases} \mathrm{e}^{\sum_{i=0}^{3}\sum_{j=0}^{3}(L_{i,j}^{e}\times v_i \times u_j)} & \text{for } \alpha \geq 0 \\ \mathrm{e}^{\sum_{i=0}^{3}\sum_{j=0}^{3}(\mathrm{M}_{i,j}^{e}\times v_i \times u_j)} & \text{for } \alpha < 0 \end{cases} \tag{7}$$

where,

$L_{i,j}^{e},\ \mathrm{M}_{i,j}^{e}$-model regression coefficients for measure of effectiveness e at speed power i and acceleration power j

$v_i, u_i,$ as previously defined

Constraints

Besides the safety penalty in the objective function, additional constraints are required to ensure the safety performance of the controller. Without time headway constraint, the longitudinal controller may not be able to prevent overshooting: the following vehicle would likely move too close to the preceding vehicle. Therefore, a minimal headway constraint for each following vehicle is proposed. Additionally, a safety factor is also incorporated for the circumstance where communication is temporarily disrupted. The collision avoidance constraint for each vehicle is expressed as Eq. 8. For the leader of the platoon, a simple headway control algorithm whose main objective is to keep a safety headway with the preceding vehicle (shown in Eq. 9), was adapted under the assumption that vehicle gap is detected by on-board sensor.

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \geq \gamma h_{\mathrm{i,min}} \tag{8}$$

γ-additional safety factor for headway

$h_{i,\min}$-user-defined minimal headway for vehicle i, s

$x_i\,(t+1)$-bumper-to-bumper gap for vehicle i to preceding vehicle at time interval t+1, m

$v_i\,(t+1)$-instantaneous speed for vehicle i at time interval t+1, m/s

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \geq \gamma h_{LV,\min} \tag{9}$$

where,

$h_{LV,\min}$-user-defined minimum headway when becoming a platoon leader, s

$\gamma,\ h_{i,\min}\ x_i\,(t+1),\ v_i\,(t+1)$ as previously defined

CACC vehicles should be closely platooned together to maximized the short headway enabled by V2V communication. If the intra-platoon headway exceeds a certain threshold, it would be more beneficial to split the original platoon into two and each platoon conducts its own optimization. In case where a non-CACC vehicle merges into the platoon, it would be difficult to perform a platoon wide optimization to consider the non-CACC vehicle in the platoon. To this end, a maximum headway constraint is expected to make the platoon more effective and robust, which can be expressed as Eq. 10. For the leader of a platoon, the effective headway does not applied at this stage to provide more flexibility for the overall platoon during optimization.

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \leq h_{\max} \tag{10}$$

where

$h_{\max}$ - user-defined maximum headway for following vehicle, s

$x_i\,(t+1),\ v_i\,(t+1)$ as previously defined

The powertrain capability (e.g. acceleration, breaking power) of a vehicle should also be considered in order to prevent the controller from yielding unrealistic acceleration commands. It is assumed that such powertrain information for each vehicle would be disseminated within platoon under CV environment. In actual deployment on the roadway, it is very likely that a heterogeneous vehicle platoon is controlled and individual vehicle powertrain constraint can be expressed as Eq.11. Typically, 3 m/s^2 rate is applied as maximum deceleration rate for field deployment and a 2 m/s^2 of acceleration could be considered as the comfortable value *(34)*.

$$u_{\mathrm{i,min}} \leq u_i \leq u_{\mathrm{i,max}} \tag{11}$$

where,

$u_{\mathrm{i,min}}$ -the minimum acceleration of vehicle i, m/s^2

$u_{\mathrm{i,max}}$ - the maximum acceleration of vehicle i, m/s^2

The last constraint is the roadway geometry constraint, including minimum and maximum travel speeds. Only speed limits are considered in this paper, as displayed in Eq. 12. These information is assumed to be either disseminated via V2I under CV environment.

$$v_{\min} \le v_i \le v_{\max} \tag{12}$$

where,

$v_{\min}$ -the minimum allowable speed on a particular roadway, m/s

$v_{\max}$ - the maximum allowable speed on a particular roadway, m/s

Due to the importance of safety, both headway constraints have to be satisfied. The physical limitation of power train should as well be a hard constraint. One may argue that speed limit should be a soft constraint, but at this stage, it was programmed as a hard constrain. In retrospect, the overall system to be optimized is shown below,

To minimize

$$[\sum_{i=1}^{n}\left|H - h_i(t+1)\right|;\ \sum_{i=1}^{n} e^{\frac{h_{i,0}}{h_i(t+1)}} \triangle v_i^2;\ \sum_{i=1}^{n} e^{\beta\frac{\left|u_i(t+1)-u_i(t)\right|}{u_{confort}}};\begin{cases} \mathrm{e}^{\sum_{i=0}^{3}\sum_{j=0}^{3}(L_{i,j}^{e}\times u^i \times a^j)} & \text{for } \alpha \ge 0 \\ \mathrm{e}^{\sum_{i=0}^{3}\sum_{j=0}^{3}(\mathrm{M}_{i,j}^{e}\times u^i \times a^j)} & \text{for } \alpha < 0 \end{cases}]$$

Subject to

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \ge \gamma h_{\mathrm{i,min}}$$

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \ge \gamma h_{LV,\min}$$

$$\frac{x_i\,(t+1)}{v_i\,(t+1)} \le h_{\max}$$

$$u_{\mathrm{i,min}} \le u_i \le u_{\mathrm{i,max}}$$

$$v_{\min} \le v_i \le v_{\max}$$

With the decision variable

$u_i(t+1)$ $-$ acceleration rate of vehicle i at next time interval $\left(\mathrm{t}{+}1\right)$

Genetic Algorithm

Inspired by the principle of natural genetics and selection, genetic algorithms (GAs) utilized the fundamental concept to perform optimization with minimal problem information *(31)*. This study used the built-in elitist multi-objective genetic algorithm (MOGA) in MATLAB. The MOGA uses a controlled elitist genetic algorithm, which is a variant of non-dominated sorting genetic algorithm II (NSGA-II) *(35)*. The NSGA-II selects individuals based on both non-dominated rank (i.e., fitness value) and distance measure of the individual in the current generation. The number of individuals in the current population is limited to 35% of the population size. After each iteration, a set of optimal solutions are obtained from the Pareto frontier which comprised of non-dominated and equally good solutions. One optimal solution based on the primary objective (e.g. mobility, safety, fuel consumption) has to be chosen. In this study, the 85th percentile of mobility was set for selection criteria.

EVALUATION

Simulation Test Bed

In order to demonstrate the effectiveness of the proposed MOOP-CACC control, proof-of-concept (POC) tests were conducted in a microscopic simulation framework, which was comprised of VISSIM and VISSIM COM Interface, and MATLAB developed in Microsoft Visual Studio environment. The high level framework architecture is shown in **Figure 1**.

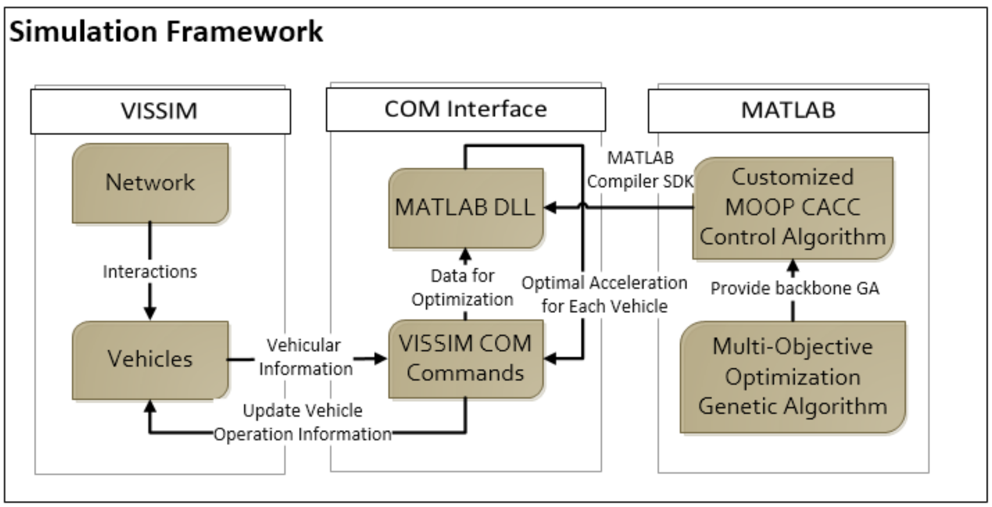


Figure 1 Simulation framework

The control algorithm was written in MATLAB script and then compiled to a Dynamic Link Libraries (DLL) for deployment in VISSIM COM Interface. During each update interval, instantaneous speed, acceleration and gaps, along with other pre-defined parameters, were input to the MOOP CACC controller (the MATMAL DLL). The output of the controller was the optimal acceleration for the next-step for each vehicle within a platoon. A hypothetical 14.5km-long freeway segment with one lane was adopted to conduct simulation experiments with following assumptions:

1. The V2V communication is perfect with no package drops and radio interference.
2. The CACC platoon to be optimized is comprised of only CACC vehicles
3. The leader of the platoon operates under the aforementioned slightly different constraints, which allows more flexible reactions to preceding vehicle as long as it is within constraints.
4. The driving behavior parameters from a calibrated VISSIM Network located in the Interstate Highway 66 located in Fairfax County, Virginia, is selected as a subset to represent human driver.

Experimental Design

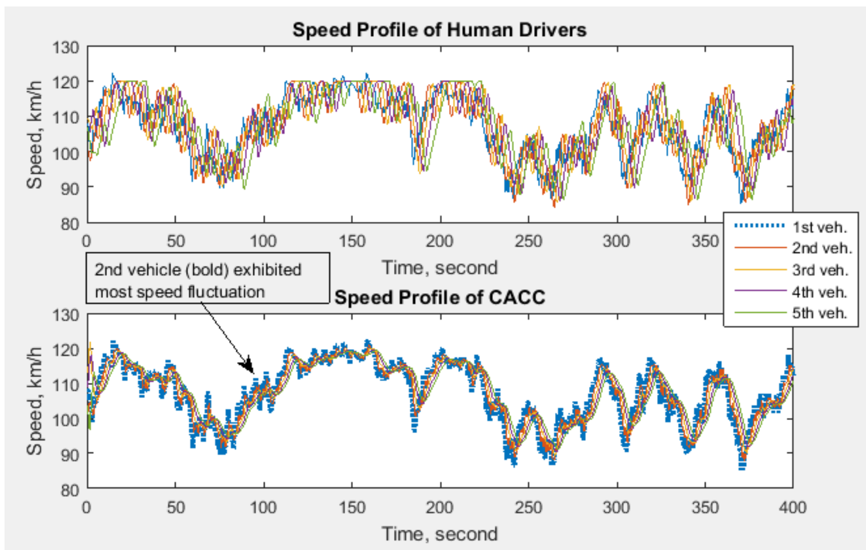
A human-driven vehicle was placed in the network work, followed by a platoon made up of 5 equipped CACC vehicles. With the feasible range of pre-determined headway, 5 CACC vehicles were set with randomized desire speeds around the speed limit. After the warning up distance of 1.2 km, all the CACC vehicles are simulated to receive command to form a platoon. The simulation resolution was set as 10, which means VISSIM computes the vehicular behavior in 0.1 second. Vehicle information, however (e.g. speed, acceleration, intra-platoon gaps) was collected in every 0.5 seconds. The MOOP controller computed the optimal acceleration for each individual vehicles within the platoon and updated the acceleration rates every 0.5 seconds. The parameters used are summarized in Table 1. Two types of experiment were conducted: 1) the validation of the MOOP-CACC compared to other vehicle controllers; 2) the analysis of output from MOOP-CACC and SOOP-CACC controllers with the same objectives. The CACC vehicle platoon is set to follow the non-CACC vehicle, whose speed profile was pre-determined. The parameters used in the simulation are listed in Table 1. Reaction for the following CACC vehicles was observed and analyzed, after 1.2 km warning up distance.

TABLE 1 Simulation Parameters

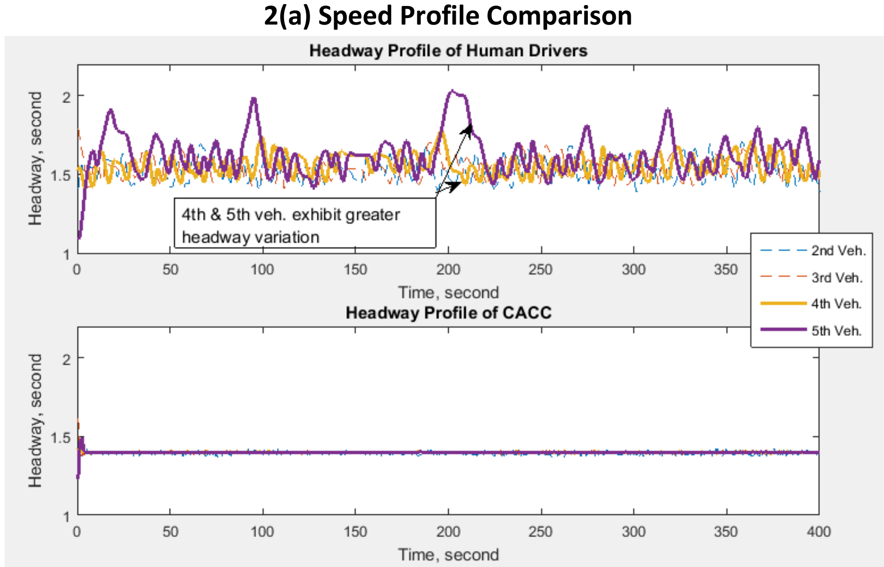
Parameter	Value	Parameter	Value
H	06, 0.9, 1.4s (depending on MOOP controllers)	$h_{LV,\min}$	1.7s
$h_{i,\max}$	2.1ss	$h_{i,\min}$	0.4, 0.6, 1.0s (depending on controller)
$h_{i,0}$	1.0s	$u_{comfort}$	1.0 m/s^2
$u_{\mathrm{i,min}}$	-3 m/s^2	$u_{\mathrm{i,max}}$	2 m/s^2
$v_{\max}$	35m/s(125 km/h)	$v_{\min}$	21m/s(75km/h)
β	1	γ	1.1

Numerical Results

The platoon behavior is shown in Figure 2. Compared to human drivers, the speed change of MOOP-CACC was more responsive to the leading vehicle with minimal delay, which indicated that the CACC vehicles were able to maintain to a coherent speed profile to enhance the string stability as shown in Figure 2(a). It was also noted that the second vehicle in CACC platoon exhibits relatively greater reaction to the leading vehicle, but it did help to dampen the propagation of shockwave to the remainder of the platoon. In response to the speed change of the leading vehicle, the 4th and the 5th vehicle of human drivers experience more fluctuations, while the vehicles in CACC platoon managed to maintain the target headway. For the 4th vehicle of human driver the standard deviation of headway was 0.069 seconds, compared to 0.003 seconds of that of MOOP-CACC; the 5th vehicle of human drive had the highest standard deviation of headway- 0.132 seconds, compared to 0.008 seconds of MOOP-CACC, as shown in Table 2.



2(a) Speed Profile Comparison



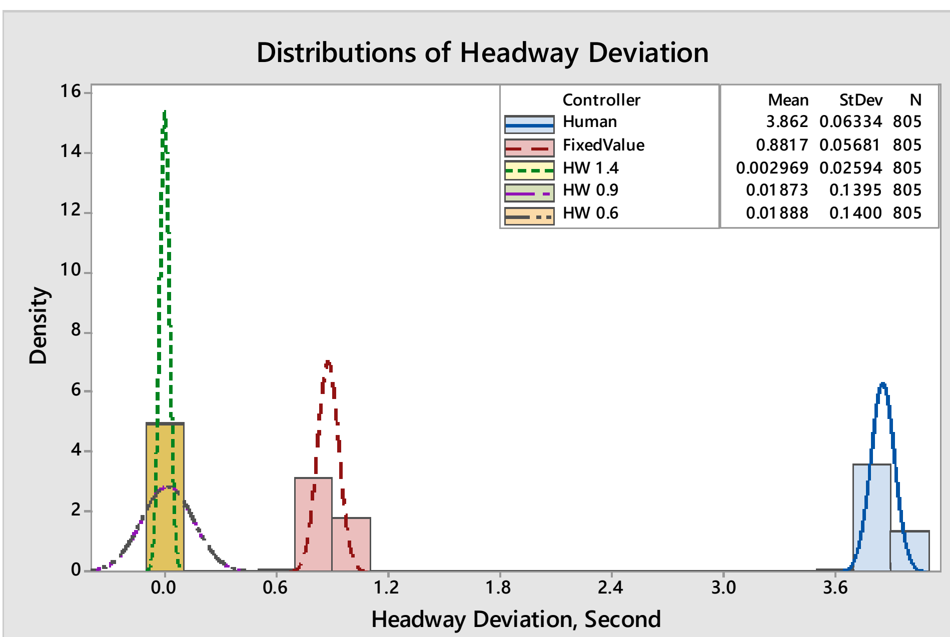
2(b) Headway Comparison

FIGURE 2 Comparison between human drivers and MOOP-CACC

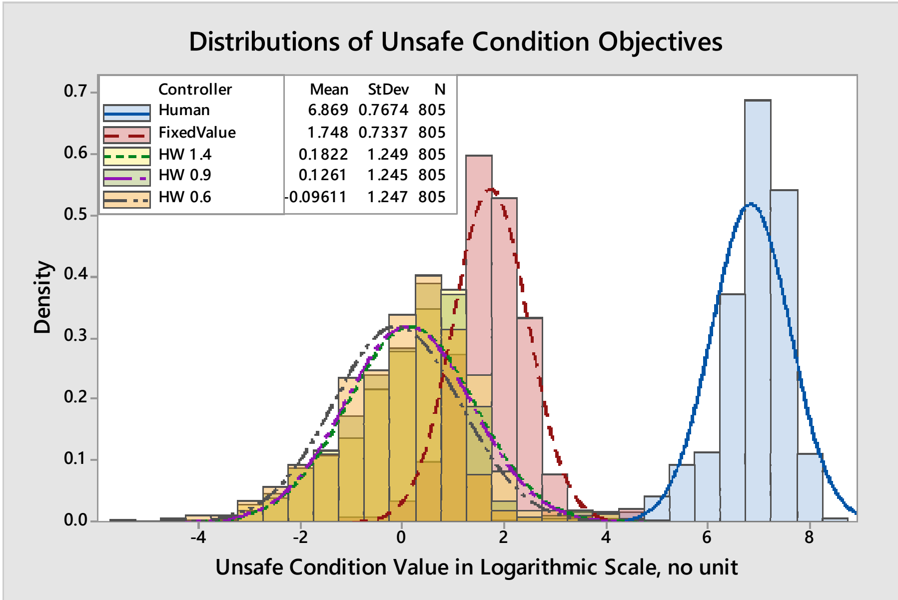
TABLE 2 Descriptive Statistics Comparison

Controller	**vehicle**	**Mean (second)**	**Difference to Target Headway**	**Std. Deviation**
MOOP-CACC	4th vehicle	1.3997	-0.0003	0.00254
	5th vehicle	1.3999	-0.0001	0.00820
Human	4th vehicle	1.5585	0.1585	0.0685
	5th vehicle	1.6191	0.2191	0.1323

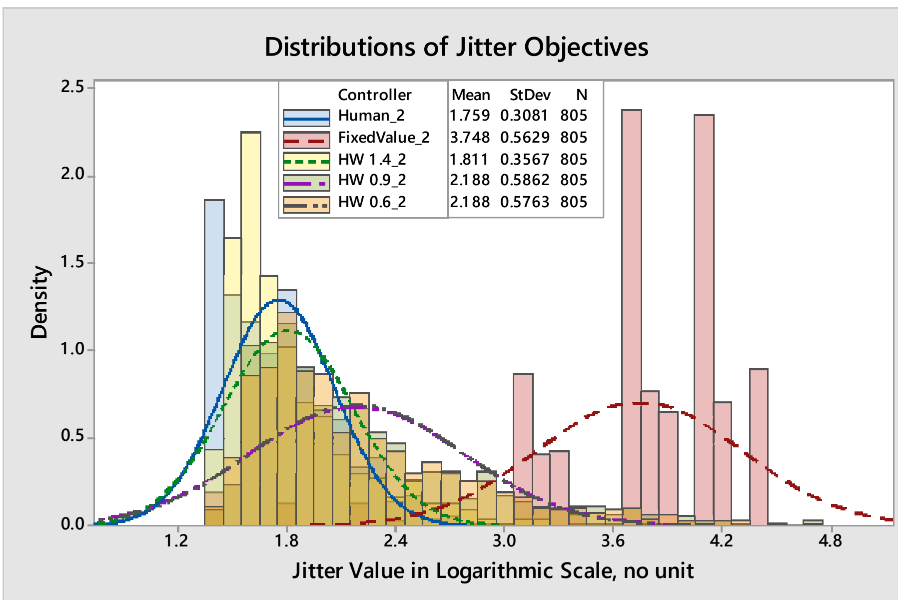
With the same simulation framework, three additional MOOP-CACC controllers are incorporated into the evaluation. The five controllers tested were: 1) Human driver (no controller); 2) FV-CACC controller proposed by Lee et al. *(5)* with discrete fixed acceleration rates; and 3) proposed MOOP-CACC with 1.4-second target headway; 4) proposed MOOP-CACC with 0.9-second target headway; and 5) proposed MOOP CACC with 0.6-second target headway. Figure 3(a) shows all three MOOP-CACC controllers converged to the target headway and maintained minimal deviations in spite of traffic disturbance. The mean headway deviation of the FV-CACC controller was 0.89 seconds, in-between of MOOP-CACC and human drivers. In Figure 3(b), it shows the human driver platoon had the highest unsafe objective value. The headway deviation of all MOOP-CACC was 0.87 seconds less than that of FV-CACC and 3.86 seconds less than that of human driver, in another word, 0.21 seconds less per vehicle and 0.97 seconds less per vehicle respectively. For the jitter objective, human driver was the lowest among all controllers, as shown in Figure 3(c). It is understandable that the foremost "objective" of human drivers is to achieve greatest riding comfort when put behind the wheel. However, it is worth noting that the mean of MOOP-CACC controller with 1.4-second headway was only 2% higher than human drivers in terms of jitter objective value. For the fuel consumption in Figure 3(d), ANOVA tests showed that the means of MOOP-CACC with 0.6-second and 0.9-second headway were statistically the same, and both of them were different than the other 3 controllers. MOOP-CACC with 1.4-second target headway has the lowest mean of fuel consumption.



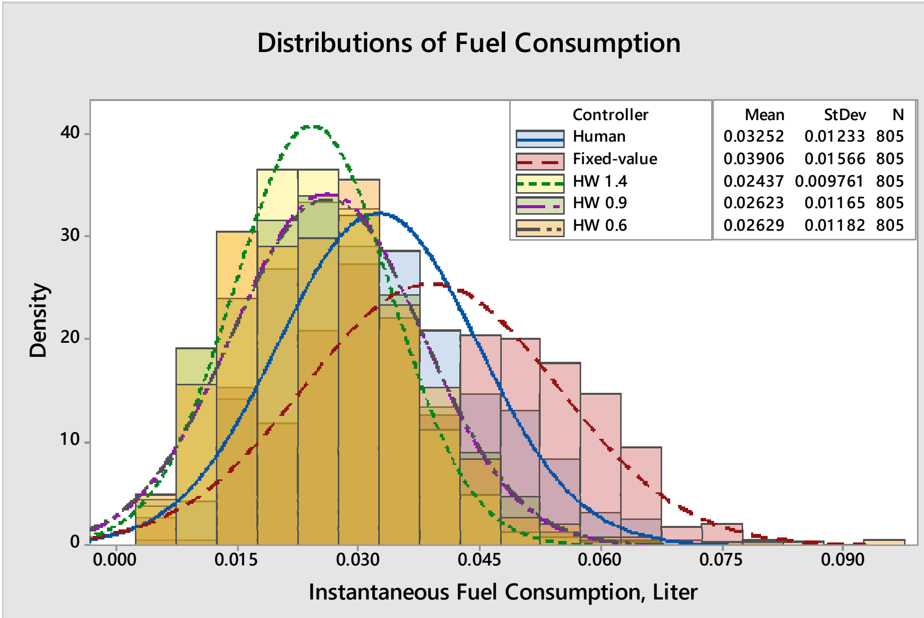
3(a) Histogram of headway deviation



3(b) Histogram of unsafe condition objective



3(c) Histogram of Jitter Objective



3(d) Histogram of instantaneous fuel consumption

FIGURE 3 Distribution of Objective Values

To investigate the performance of MOOP, four scenarios with different objective functions were designed to compare the performance of SOOP and MOOP (with 0.9 intra-platoon headway) under the same traffic condition and constraints. MOOP-1 and MOOP-2 represented that the solution with the 85th and 50th percentile optimal headway deviation values were selected from the Pareto frontier in each optimization, respectively. The SOOP-1 was the optimization performed on headway deviation objective only, while similarly the objective function of SOOP-2 dealt with unsafe condition only.

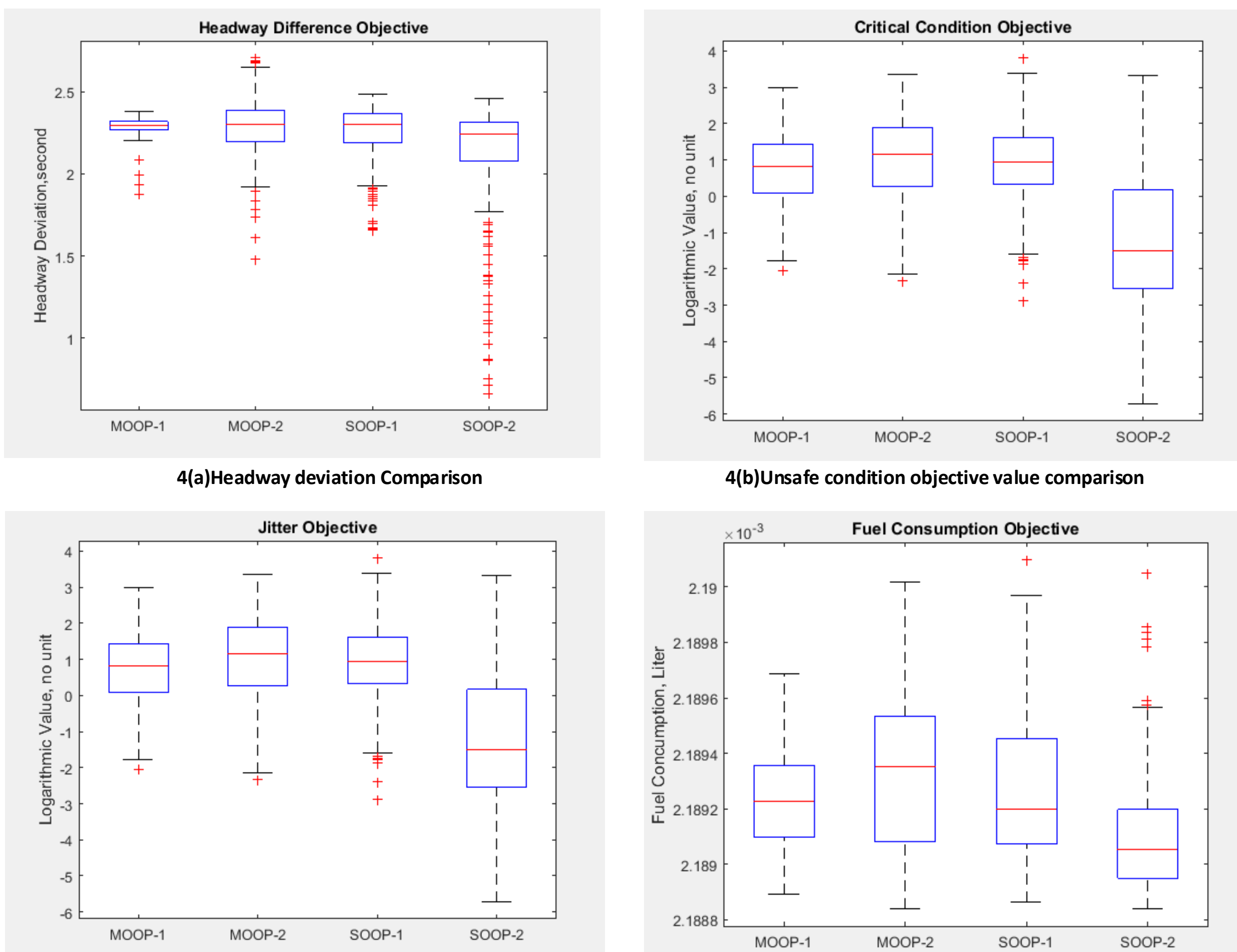
Tukey Pairwise Comparisons test with 95% confidence for all groups of objective values are shown in Table 3, where mean values that do not share a letter are considered significantly different. For headway deviation objective, the value of SOOP-2 was statistically different from three of its peers. For the Unsafe condition objective, MOOP-2 and SOOP-1 were the same, while the value of MOOP-1 and SOOP-2 were belong to two different groups. With respect to Jitter, each of the objective values were significantly different. And for the fuel consumption objective values, MOOP-1, MOOP-1, and SOOP-2 belonged to separate group, while SOOP-1 could be consider share the same group with either MOOP-1 or MOOP-2.

TABLE 3 Tukey Pairwise Comparison Tests

Headway Deviation Objective				**Unsafe Condition Objective**			
Method	**Mean**	**Std. Deviation**	**Grouping**	**Method**	**Mean**	**Std. Deviation**	**Grouping**
MOOP-1	2.286	0.0525	A	MOOP-1	0.7339	0.9499	B
MOOP-2	2.2896	0.1691	A	MOOP-2	1.0404	1.0372	A
SOOP-1	2.25452	0.1613	A	SOOP-1	0.8314	1.1048	A
SOOP-2	2.1271	0.3354	B	SOOP-2	-1.215	1.857	C
Jitter Objective				**Fuel Consumption Objective**			
Method	**Mean**	**Std. Deviation**	**Grouping**	**Method**	**Mean**	**Std. Deviation**	**Grouping**
MOOP-1	3.1238	1.0928	C	MOOP-1	0.002189	0.0000	B

MOOP-2	4.2379	0.567	A	MOOP-2	0.002189	0.0000	A
SOOP-1	3.5557	1.2033	B	SOOP-1	0.002189	0.0000	A,B
SOOP-2	1.4748	0.2716	D	SOOP-2	0.002189	0.0000	C

In addition, each of the objective was calculated and plotted in boxplots in Figure 4. As seen, the objective function values have more outliners in both SOOP scenarios. SOOP-2 outperformed two MOOPs in minimizing unsafe condition, due to the fact that the objective function was designed to solely minimize the unsafe condition. However, the standard deviation of SOOP-2 was 0.28 seconds more than that of MOOP-1 in with respect to target headway deviation and approximately 97% higher in unsafe condition than MOOP-1. Similarly, SOOP-1 also experienced higher standard deviation in objective values. The higher the standard deviation, the less stable the platoon is. It is also worth noting that SOOP-1 seemed perform worse that SOOP-2 by comparing the mean values. However, the standard deviation of SOOP-1 was only half of that of SOOP-2, which indicated SOOP-1 performed more consistently and batter than SOOP-2. Hence, both MOOP controllers appeared to have better Pareto-optimality. We can also conclude that the MOOP-1 performed better than MOOP-2 with all aspect considered.



4(a)Headway deviation Comparison

4(b)Unsafe condition objective value comparison

4(c) Jitter objective value comparison

4(d) Instantaneous fuel consumption comparison

FIGURE 4 Boxplot for Objective Value Comparison

CONCLUDING REMARKS

An innovative MOOP-CACC controller was proposed in this paper. To systematically evaluate the proposed algorithm, a generic simulation framework was developed by integrating VISSIM, MATLAB, and VISSIM COM Interface for transportation simulation, algorithm development, and algorithm implementation, respectively. Based on the simulation tests conducted, the target headway deviation of all MOOP-CACC was on average 0.96 seconds less than that of human driver. It also successfully dampened the speed fluctuation caused by human drivers. For the last vehicle within a platoon, MOOP-CACC achieved 0.001-second deviation of target headway (with a standard deviation of 0.00820 seconds), while the human driver was only able to maintain a 0.22-second deviation in target headway (with a standard deviation of 0.1323 seconds).

In addition, variants of the MOOP-CACC controllers (e.g. 1.4-, 0.9-, and 0.6-second target headway) were tested. With both 0.9- and 0.6-second cases performed statistically the same, the simulation results showed that MOOP-CACC with 0.9-second target headway marginally yielded the better performance in targeted headway deviation and instantaneous fuel consumption. However, 0.6-seond MOOP-CACC is expected to provide more increase in the overall carrying capacity than the 0.9-second case. Compared to a previously developed CACC algorithm (i.e. FV-CACC), the MOOP-CACC exceeded FV-CACC in all aspects: a 98% reduction in headway deviation objective, a 93% reduction in unsafe condition objective, a 42% reduction in Jitter objective, and a 33% reduction in instantaneous fuel consumption.

Furthermore, the comparison between MOOP- and SOOP- CACC showed that MOOP kept a good balanced among all the objective and hence produce better Pareto-optimality. On the contrary, both SOOP-CACCs generated higher standard deviations: 0.28 seconds higher in target headway deviation and approximately 97% higher in unsafety condition, respectively. It is also observed that SOOP-CACC showed difficulties in balancing the overall system objectives and it was likely subjected to bias or personally preference, which could limit the search space of the optimization.

The future research will be focused on addressing the assumptions made in the POC test. First, the perfect V2V communication is unlikely in the real-word scenario. A fail-safe algorithm dealing with imperfect communication environment should be developed. Secondly, the algorithm should be evaluate along with a wireless communication simulator with a more realistic updating interval (e.g. higher than 10Hz). Thirdly, more comparisons with another CACC controllers need to be made to evaluate the proposed algorithm from all aspects. Lastly, the proposed algorithm need to be tested on a well-calibrated realistic simulation network for even more comprehensive evaluation.

REFERENCE

(1) Scharank D, Eisele B, Lomax T. TTI's 2012 Urban Moblity Report. The Tesac A&M University System: 2012.

(2) USDOT. Connected Vehicle: CV Pilots Deployment Project 2015 [cited 2015 April 28th]. Available from: http://www.its.dot.gov/pilots/cv_pilot_progress.htm.

(3) Barbaresso J, Gordahi G, Garcia D, Hill C, Jendzejec A, Wright K. USDOT's Intelligent Transportation Systems (ITS) ITS Strategic Plan 2015-2019. ITS Joint Program Office, 2014 FHWA-JPO-14-145.

(4) Wang M, Treiber M, Daamen W, Hoogendoorn SP, van Arem B. Modelling Supported Driving as an Optimal Control Cycle: Framework and Model Characteristics. Procedia - Social and Behavioral Sciences. 2013;80(0):491-511.

(5) Lee J, Bared J, Park BB. Mobility Impact of Cooperative Adaptive Cruise Control (CACC) under Mixed Traffic Conditions. 93rd TRB Annual Meeting; Washington DC, USA2014.

(6) Wang M, Daamen W, Hoogendoorn SP, van Arem B. Rolling horizon control framework for driver assistance systems. Part I: Mathematical formulation and non-cooperative systems. Transportation Research Part C: Emerging Technologies. 2014;40(0):271-89.

(7) Wang M, Daamen W, Hoogendoorn SP, van Arem B. Rolling horizon control framework for driver assistance systems. Part II: Cooperative sensing and cooperative control. Transportation Research Part C: Emerging Technologies. 2014;40(0):290-311.

(8) van Arem B, Driever H, Feenstra P, Ploeg J, Klunder G, Wilmink I, et al. Design and evaluation of an integrated full-range speed assistant. Summary of research, TNO Traffic and Transport. 2007.

(9) Yu S, Shi Z. The effects of vehicular gap changes with memory on traffic flow in cooperative adaptive cruise control strategy. Physica A: Statistical Mechanics and its Applications. 2015;428(0):206-23.

(10) Zhang HM. A mathematical theory of traffic hysteresis. Transportation Research Part B: Methodological. 1999;33(1):1-23.

(11) Helly W, editor Simulation of Bottlenecks in Singal Lane Traffic Flow Symposium on Theory of Traffic Flow; 1959; New York: Elsevier.

(12) Treiber M, Hennecke A, Helbing D. Congested traffic states in empirical observations and microscopic simulations. Physical Review E. 2000;62(2):1805-24.

(13) Li Z, Li W, Xu S, Qian Y. Stability analysis of an extended intelligent driver model and its simulations under open boundary condition. Physica A: Statistical Mechanics and its Applications. 2015;419(0):526-36.

(14) Montanaro U, Tufo M, Fiengo G, di Bernardo M, Salvi A, Santini S, editors. Extended Cooperative Adaptive Cruise Control. Intelligent Vehicles Symposium Proceedings, 2014 IEEE; 2014 8-11 June 2014.

(15) Ge JI, Orosz G. Dynamics of connected vehicle systems with delayed acceleration feedback. Transportation Research Part C: Emerging Technologies. 2014;46(0):46-64.

(16) Arnaout G, Bowling S. A progressive deployment strategy for cooperative adaptive cruise control to improve traffic dynamics. Int J Autom Comput. 2014;11(1):10-8.

(17) Chan E, editor SARTRE Automated Platooning Vehicles. Transport Research Arena 2014; 2014; Paris, France.

(18) Rajamani R, Shladover SE. An experimental comparative study of autonomous and co-operative vehicle-follower control systems. Transportation Research Part C: Emerging Technologies. 2001;9(1):15-31.

(19) Fanping B, Han-Shue T, Jihua H, editors. Design and field testing of a Cooperative Adaptive Cruise Control system. American Control Conference (ACC), 2010; 2010 June 30 2010-July 2 2010.

(20) Omae M, Fukuda R, Ogitsu T, Chiang W-P. Control Procedures and Exchanged Information for Cooperative Adaptive Cruise Control of Heavy-Duty Vehicles Using Broadcast Inter-Vehicle Communication. Int J ITS Res. 2014;12(3):84-97.

(21) Milanes V, Shladover SE, Spring J, Nowakowski C, Kawazoe H, Nakamura M. Cooperative Adaptive Cruise Control in Real Traffic Situations. Intelligent Transportation Systems, IEEE Transactions on. 2014;15(1):296-305.

(22) Alam A, Gattami A, Johansson KH, Tomlin CJ. Guaranteeing safety for heavy duty vehicle platooning: Safe set computations and experimental evaluations. Control Engineering Practice. 2014;24(0):33-41.

(23) van Nunen E, Kwakkernaat RJAE, Ploeg J, Netten BD. Cooperative Competition for Future Mobility. Intelligent Transportation Systems, IEEE Transactions on. 2012;13(3):1018-25.

(24) Nieuwenhuijze MRI, van Keulen T, x, ncu, x, S., et al. Cooperative Driving With a Heavy-Duty Truck in Mixed Traffic: Experimental Results. Intelligent Transportation Systems, IEEE Transactions on. 2012;13(3):1026-32.

(25) Bergenhem C, Hedin E, Skarin D. Vehicle-to-Vehicle Communication for a Platooning System. Procedia - Social and Behavioral Sciences. 2012;48(0):1222-33.

(26) Ploeg J, Serrarens AA, Heijenk G. Connect & Drive: design and evaluation of cooperative adaptive cruise control for congestion reduction. J Mod Transport. 2011;19(3):207-13.

(27) Wu Z, Flintsch G, Ferreira A, Picado-Santos L. Framework for Multiobjective Optimization of Physical Highway Assets Investments. Journal of Transportation Engineering. 2012;138(12):1411-21.

(28) Wu W, Gan A, Cevallos F, Hadi M. Multiobjective Optimization Model for Prioritizing Transit Stops for ADA Improvements. Journal of Transportation Engineering. 2011;137(8):580-8.

(29) Meng Q, Khoo HL. A Pareto-optimization approach for a fair ramp metering. Transportation Research Part C: Emerging Technologies. 2010;18(4):489-506.

(30) Abdelgawad H, Abdulhai B, Wahba M. Multiobjective Optimization for Multimodal Evacuation. Transportation Research Record: Journal of the Transportation Research Board. 2010;2196(-1):21-33.

(31) Deb K. Multi-Objective Optimization using Evolutionary Algorithms: Sharda Offset Press, Delhi; 2010.

(32) Tan TG, Teo J, Chin KO. Single-versus Multiobjective Optimization for Evolution of Neural Controllers in Ms. Pac-Man. International Journal of Computer Games Technology. 2013;2013.

(33) Rahka H, Ahn K, Trani A. Development of VT-Micro Model for Estimating Hot Stabilized Light Duty Vehicle and Truck Emissions. Transportation Research Part D: Transport and Environment. 2004:49-74.

(34) VanderWerf J, Shladover S, Kourjanskaia N, Miller M, Krishnan H. Modeling Effects of Driver Control Assistance Systems on Traffic. Transportation Research Record: Journal of the Transportation Research Board. 2001;1748(-1):167-74.

(35) Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. Evolutionary Computation, IEEE Transactions on. 2002;6(2):182-97.