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Modeling Multi-Objective Optimization Algorithms for Autonomous Vehicles to Enhance Safety and Energy Efficiency

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ABSTRACT

Multiple optimization controls are associated with autonomous vehicles' movement. These control systems are employed to enhance the comfort of passengers in commercial vehicles or to avoid enemy areas for unmanned military convoys. However, having multiple objectives for optimization can greatly enhance the perception and applicability of these algorithms. This paper involves demonstrating a multi-layered optimization framework which can achieve both and efficiently navigate autonomous vehicles. Other than the primary objective of reducing the probability of intersection crashes, minimizing individual vehicle delay and additionally minimizing energy consumption are the objectives of this example. Primarily this application consists of two parts: a multi-objective optimization framework and individual mathematical models that define vehicle parameters at intersections including vehicle dynamics model and vehicle energy consumption models. Such optimization framework could enhance driving algorithms of militarized convoys. Look-ahead controls would help them optimize both their distance as well as their energy consumption, thereby increasing convoy range and operational energy efficiency as well as decreasing costly convoy halts.

INTRODUCTION

Autonomous cars area is one of the fastest growing research segment in the transportation and automobile industry, one of the primary boosts to which is the Vehicle Infrastructure Integration that will let cars "talk" to each other and with road-side devices. In the United States, Connected Vehicle Program aims at bringing this connectivity by providing V2X (vehicle-to-vehicle or V2V and vehicle-to-infrastructure or V2I) communication and are being deployed for test purposes. Among the handful of connected vehicle/autonomous vehicle research, one of the systems proposed was an ICACC system which stands for Intersection Management using Cooperative Adaptive Cruise Control and aims at optimizing vehicle's speed profiles to minimize delay and prevent crashes at intersections [1]. This research has shown potential fuel savings when delay is minimized and uses automated longitudinal control to replace conventional signal control to allow vehicles to time themselves to arrive at an intersection to pass safely. Another proposed system, Eco-Cooperative Adaptive Cruise Control (ECACC), aimed at optimizing vehicle's speed profiles to minimize the fuel consumed by vehicles at an intersection [2]. It was shown that up to 30 percent fuel can be saved using the optimized speed profile and uses path-finding algorithm based dynamic programming to find a least-fuel consumed path between two speed states. This research aims at bringing these optimization algorithms together by using a bi-level optimization framework to have a combined algorithm which optimizes the vehicle behavior at intersections for minimum delay and minimum energy use. The first layer uses delay optimization logic along with crash avoidance to time the vehicle arrivals at the stop-line. Secondly, fuel-optimization logic generates a speed-profile for each vehicle for this arrival using dynamic programming. Preliminary analysis done using agent-based simulations revealed delay benefits of around 82 percent and fuel benefits of around 79 percent compared to conventional intersections. This approach is presented as a use-case to multi-objective optimization techniques using individual and independent optimization algorithms.

BACKGROUND

Specifically, the use-case defined in this paper optimizes vehicle movements through a traditional four-legged intersection to minimize delay and fuel consumption assuming that there is continuous data exchange between the vehicles about their instantaneous locations, speed and acceleration. This assumption is valid in the context of Connected Vehicle Program where vehicles continuously broadcast their "states" as Basic Safety Messages at deci-second interval. In order to develop the proposed framework, the two independent algorithms for delay and fuel optimization used mathematically modeled vehicle parameters. This includes models which govern the vehicle's speed and acceleration characteristics (vehicle dynamics model), models for vehicle's energy and emissions calculations (fuel consumption models) along with other models for vehicle's crash-avoidance and free-flow behavioral characteristics. These models are described in the following sub-sections.

Optimization Models Used

The delay minimization model is derived from [1] and uses a moving horizon optimization approach to modify vehicle arrivals at the stop-line and their arrival speeds. In principle, vehicles that are approaching an intersection from a distance will register with the optimization system which will in turn optimize their arrivals by adjusting their trajectories so that they arrive at the intersection with least delay and traverse the intersection without crashing. Full model description is given in Reference [1]. Eco-Speed Control model, proposed in [2] is used as the fuel minimization model in this paper. This model uses a modified A-star algorithm to modify trajectories of vehicles within the vicinity of an intersection to find the "least-cost" path of vehicles, which translates to minimum fuel consumption. The optimization framework is developed by comparing discretized upstream and downstream solution space using two control variables: deceleration (as a function of brake-pedal level) and acceleration (as a function of gas-pedal level). Full model description is given in Reference [2]

Other Underlying Models

The vehicle dynamics model uses vehicle-specific parameters to compute tractive and resistive forces acting on a moving vehicle and hence determines instantaneous possible acceleration and speed. In this approach, we use Rakha and Lucic vehicle dynamics model [3] to predict the maximum vehicle acceleration. It computes tractive forces based on vehicle power, gear ratios, driveline efficiency, roadway friction etc. and resistive forces based on aerodynamic, rolling and grade resistance forces. Specific equations pertaining to this model are available in [3]. VTCPFM (Virginia Tech Comprehensive Power-based Fuel Model defined in [4] is used as the fuel consumption model in this paper. This power-based fuel model utilizes instantaneous power as well as calibrated parameters from EPA cycles to compute instantaneous fuel consumption. Full description of the model is given in [4]. Vehicle behavioral models are used as part of the agent-based simulation framework that is used to assess the proposed algorithm and includes a car-following and crash-avoidance model. This research uses Rakha-Pasumarthy-Adjerid (RPA) vehicle longitudinal model [5] that includes a vehicle dynamics model for constraining vehicle accelerations, the Van Aerde steady-state car-following model and a collision avoidance model. The model doesn't include a lane-changing model and therefore assumes no lane-changes.

METHODOLOGY

Specifically, the optimization framework presented in this paper aims at optimizing vehicle movements through an intersection using trajectory alterations. Instead of traditional signal-based systems, the vehicles are assumed to have 100 percent connectivity to an intersection manager which performs trajectory alteration based on the optimization framework and controls the vehicles to follow this trajectory. The bi-level optimization framework is developed in a sequential optimization manner where firstly, the algorithm generates vehicle arrival times and intersection-entry speed for all vehicles by optimizing the delay and checking for crashes. Secondly, the algorithm generates a fuel-efficient speed profile for this particular set of constraints using dynamic programming. As in the underlying algorithms, we assume driving agents instead of human drivers to not consider human perception reaction behavior from the model. Figure 1 demonstrates the two levels of optimization in the framework.

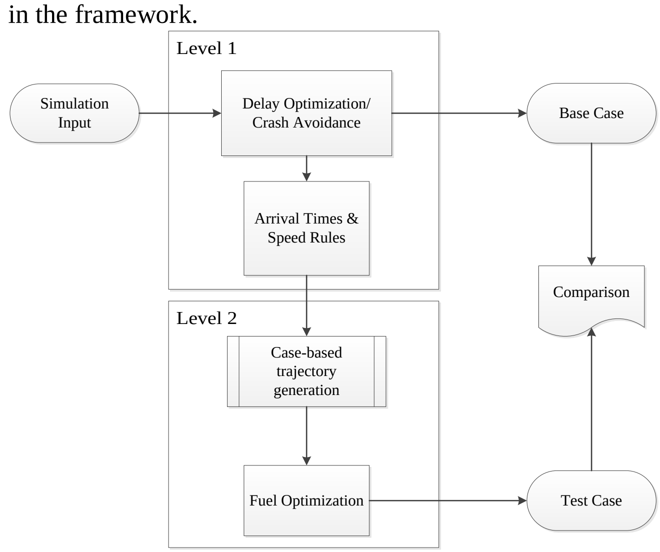

Figure 1 – Bi-level Optimization Framework

Firstly, the delay optimization module optimizes the vehicle profiles for minimum delay and crash avoidance using the principles in [1]. This takes place in three steps as shown in Figure 2:

i. All vehicles accelerate to the maximum speed at the first anchor point (upstream),
ii. Then they incorporate the required delays to separate their arrival time at the stop-line by a safety interval (to avoid crashes), and
iii. Accelerate back to maximum speed at the stop-line and proceed through the intersection.

It has to be noted that the maximum speed of each vehicle passing through the intersection depends on their turn movement. Through vehicles will have a higher speed in the intersection that the turning vehicles. The result of this layer is a speed-profile that correspond to minimum delay and that prevents crash. However, as long as vehicles maintain its time of arrival at the stop-line and the speed of passing through the intersection, this delay is conserved. Hence these are the inputs to the next level.

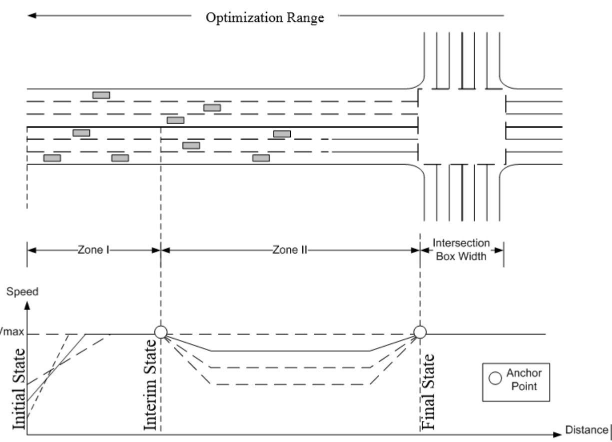

Figure 2 – Optimization Range and Optimization Actions.

In the second level, a case-based trajectory generation is used to generate a fuel optimum profile to fit each vehicle. All vehicles are divided into two sets based on whether they accelerate or decelerate. The vehicles that need to incorporate a delay in its trajectory before reaching the stop-line at maximum speed need to decelerate and then accelerate to the maximum speed and the ones that need not incorporate a delay will just accelerate to its maximum speed prior to stop-line. A dynamic programming based approach is used to optimize the trajectory for each of these cases. Specifically, a modified version of A-star path-finding algorithm is used to compute the trajectory corresponding to these constraints by defining the different states of the vehicle during its motion.

Consider a vehicle whose speed-profile is to be optimized for a given initial speed, final speed (at stop-line) and the arrival time at the stop-line (as provided by the previous layer of optimization). Figure 2 shows the three states the vehicle has to pass through during its upstream motion:

i. Initial State is defined at the initial speed of the vehicle when the optimization starts.
ii. Interim State is defined at the first anchor point where the vehicle accelerates to the maximum speed before the delay injection occurs.
iii. Final State is defined at the second anchor point (or the stop-line) when the vehicle is at its maximum speed. The time period for this state is defined by the delay optimization module.

In addition to traveling through these states, the vehicle is subject to two physical constraints: (i) a fixed distance to be covered in the given arrival time at the stop-line and (ii) fixed final speed to be achieved at the end of the maneuver. The speed, time and position of these states are fixed. The optimized profile between these states is generated using the A-star algorithm while constrained by microscopic traffic flow models as defined previously. A-star algorithm uses a recursive path-finding logic in which the optimum state advances each time-step by selecting the state that correspond to least cost to reach that state plus a heuristic estimate of the future cost it will incur by taking that state. For example, if a vehicle has to accelerate from a speed 0 km/h to 50 km/h, the speed chosen for each time-step is selected from the possible speeds by factoring the future fuel consumed resulting from the action for this time-step.

ANALYSIS AND RESULTS

In order to test the effectiveness of the proposed multi-objective optimization algorithm, a generic four legged intersection was simulated for 8 different street volumes for the major and minor streets. Each approach had three lanes with dedicated left, through and right movements and a speed limit of 35 miles per hour. The simulation was done in a MATLAB environment with traffic flow models replicating INTEGRATION simulation software. In order to calibrate the vehicle models, characteristics of a 2010 Honda Civic was used.

Table 1 - Physical Parameters of a 2010 Honda Civic

Parameter	Value
Drag Coefficient (Cd)	0.30
Frontal Area (m2)	2.32
Engine Efficiency	0.92
Percentage Mass on Tractive Axle	0.60
Mass (kg)	1453
Power (kW)	132

The simulation analysis used three cases to simulate the eight volume scenarios. They are: (i) Non-optimum Case, where a normal signalized intersection was simulated, (ii) 1st Level Optimization Case, where only delay is optimized and (iii) 2nd Level Optimization Case, where the proposed multi-objective optimization was simulated representing optimization of delay and fuel consumption. A fixed turn percentage of 20 percent to both left and right was used.

Maximum speed in the intersection is constrained by the turn movement for each vehicle with the through vehicles can pass at speed-limit and left and right turning vehicles pass at 80 and 60 percent of the speed-limit. The cases were simulated in a customized agent-based model developed in MATLAB.

Two measures of effectiveness (MOEs) were tested for each of these scenarios between the three cases - average delay per vehicle and average fuel consumed per vehicle. Since the arrival-times and speed-rules from first-level optimization (1) are used for the second-level optimization (2), the delay or travel-time values for those would be same. Hence only average fuel per vehicle is compared between these. Table 2 shows the simulation results for the three cases. It shows that the proposed multi-objective optimization cause an average fuel savings of around 79 percent and average delay reduction of around 82 percent with respect to a non-optimum case (0). Average fuel savings of around 11 percent was found with respect to just optimizing the delay ((2) versus (1)).

Table 2 – Simulation Results and Scenarios Analyzed.

Scenario	Major Volume (vph)	Minor Volume (vph)	Traditional Case (0)		First Level Optimization (1)		Second Level Optimization (2)		Delay Savings	Fuel Savings	
			Avg Delay/ Veh (s)	Avg Fuel/ Veh (l)	Avg Delay/ Veh (s)	Avg Fuel/ Veh (l)	Avg Delay/ Veh (s)	Avg Fuel/ Veh (l)	(1) vs (0)	(1) vs (0)	(2) vs (1)
1	600	300	11.8	0.085	1.2	0.0216	1.2	0.0193	89.83%	74.59%	10.65%
2	800	400	13.4	0.094	2.1	0.022	2.1	0.0197	84.33%	76.60%	10.45%
3	1000	500	14.1	0.09	2.7	0.0222	2.7	0.0199	80.85%	75.33%	10.36%
4	1200	600	16.1	0.097	3.3	0.0225	3.3	0.0201	79.50%	76.80%	10.67%
5	1400	700	15.7	0.094	3.7	0.0227	3.7	0.0204	76.43%	75.85%	10.13%
6	1600	800	19.5	0.095	4.2	0.0229	4.2	0.0205	78.46%	75.89%	10.48%
7	1800	900	21	0.097	5.2	0.0233	5.2	0.0206	75.24%	75.98%	11.59%
8	2000	1000	26.4	0.098	4	0.0229	4	0.0204	84.85%	76.63%	10.92%

Figure 3 shows the average fuel consumption per vehicle for all the three cases analyzed. As shown, there is considerable difference in fuel consumption between Case 0 and Case 1 owing to the fact that there is considerable difference in average vehicle delay (Figure 4). The average value of reduction in fuel consumption per vehicle is around 75 percent for Case 1 with respect to Case 0. Case 1 itself presents an optimized case of vehicle delay. Case 2 optimizes the vehicle trajectory to conserve this delay and minimize fuel further. As shown, the additional level of optimization reduces the fuel consumption further by more than 10 percent.

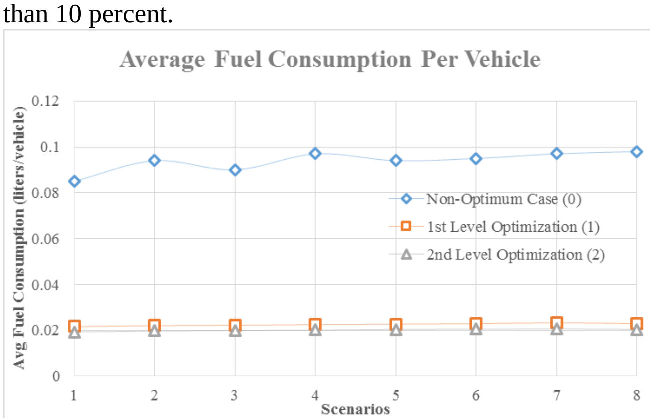

Figure 3 - Plots of Average Fuel Consumption Per Vehicle Under Different Cases and Scenarios.

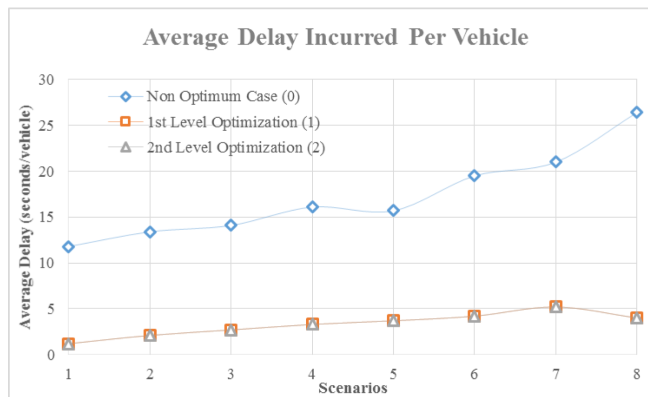

Figure 4 – Plot of Average Delay Incurred Per Vehicle Under Different Cases and Scenarios

Figure 4 shows the average delay incurred per vehicle for all the three cases analyzed. As shown, Case 1 and Case 2 provide same results in terms of average delay pertaining to the fact that Case 1 and Case 2 utilizes the same vehicle arrival times at the stop-line, thereby conserving delay in the 2nd level of optimization. The overall reduction in delay was found to be between 75 and 90 percent.

The multi-objective optimization was case-based and divided vehicle profiles according to whether there has to be a positive speed-change prior to the intersection or a negative speed-change. Negative speed-change indicates the cases in which the vehicles have to decelerate before they accelerate to the maximum possible speed in order to honor the crash-avoidance constraint in the first level of optimization. Figure 5 shows the comparison of average fuel usage by vehicles in the cases where they have a positive speed-change or a negative speed change. The average reduction in the fuel usage for cases with positive speed change was 8.57 percent and for the cases with negative speed change was 11.59 percent. This trend was because the fuel-optimization algorithm has greater room to optimize when the speed-profile involves a deceleration and acceleration as supposed to when it has just acceleration.

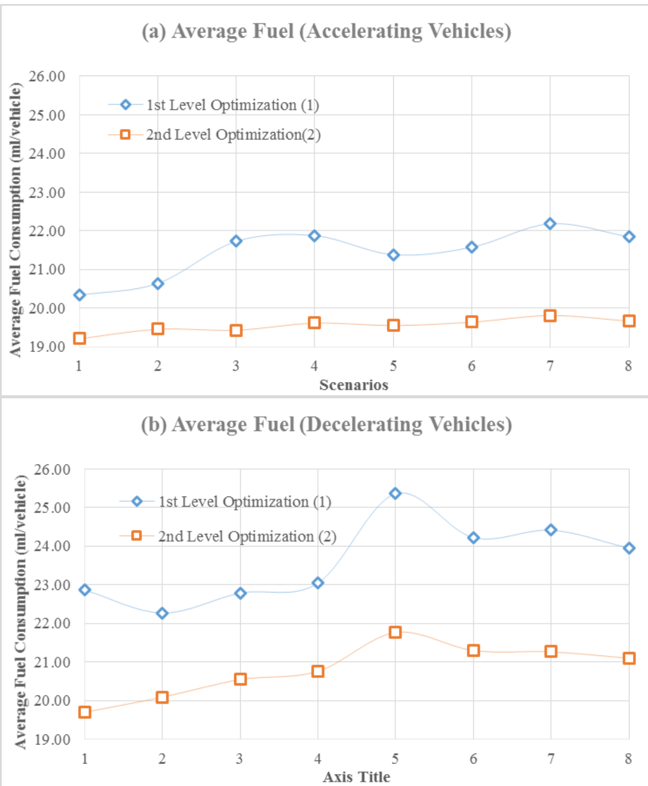

Figure 5 – Case-based analysis of fuel savings of multi-objective optimization.

CONCLUSIONS

The research presented in this paper provides a novel approach to multi-objective optimization using independent and individual optimization controls. An intersection management of vehicles that have automated longitudinal control tool was presented as use-case. The proposed algorithm works on two levels and aims at preventing crashes, minimizing overall delay at an intersection and minimizing the total fuel consumed at an intersection. At the first level, the algorithm generates vehicle arrival times at the stop-line along with an associated speed which corresponds to optimized delay and crash avoidance. In the second level, the algorithm generates a fuel-optimized velocity profile for vehicles to follow this constraint. The multi-objective optimization approach was able to save around 10 to 11 percent fuel over the delay-optimization approach. This is in addition to the 76 percent fuel it already saves over the non-optimum case. The proposed approach reduces the average delay by 82 percent when compared to non-optimum intersection control. Case-based analysis of vehicles that just accelerates prior to stop-line and that decelerates before acceleration to incorporate a delay shows that a vehicle that merely accelerates saves lesser fuel than the other. However, the absolute fuel usage by vehicles that accelerate is lesser than those which decelerates before accelerates.

The multi-objective optimization tool presented and tested in this paper warrants further analysis to modify and test this approach. Such optimization framework could enhance driving algorithms of militarized convoys. Look-ahead controls would help them optimize both their distance as well as their energy consumption, thereby increasing convoy range and operational energy efficiency as well as decreasing costly convoy halts.

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