2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)
Windsor Oceanico Hotel, Rio de Janeiro, Brazil, November 1-4, 2016

An Overview of Driver Feedback Systems for Efficiency and Safety

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Abstract— **Driver feedback systems have the potential to improve driving safety and efficiency by providing instructions to drivers aimed at improving their driving style. There is already a rich body of available literature devoted to the derivation of energy efficient speed profiles to develop driver feedback or eco-driving systems. While most of them can be applied to any type of vehicle, their effectiveness will be maximized if their formulation involves the dynamics of the particular vehicle powertrain configuration. This paper summarizes the research trends in the development of these systems that have been reported in the literature to date classifying them according to the powertrain structure and the nature of the control strategy. The study concludes with a discussion on the remaining challenges and potential future research directions.**

I. Introduction

The increasing challenges posed by traffic congestion and accidents are stimulating the investigation of new approaches for improved driving control. One promising approach is based on the concept of using enhanced driver feedback to improve overall vehicle and traffic network performance. Driver responses to traffic disturbances are a significant cause of congestion and safety issues [1]. As a result, driver behavior has been a key contributor to the 2.2 million nonfatal injuries, 35,000 deaths and estimated 1.7 billion metric tons of CO_2 released to the environment in 2012 [2]. In 2014, congestion caused people in urban areas to spend 6.9 billion hours more on the road and to purchase an extra 3.1 billion gallons of fuel, resulting in a total cost estimated at $160 billion [3]. Limitations in mobility generate driver frustration, irritation, and stress, which may encourage more aggressive driving behavior and further slow the process of recovering free traffic flow [4]. Thus it is becoming increasingly clear that driver behavior should be a key concern in developing more sustainable transportation technologies.

There is a solid body of research now available on various approaches for optimizing vehicle system efficiency both for conventional [5] and hybrid powertrain systems [6]. There have been also several studies that have considered improving transportation efficiency through coordination of connected automated vehicles (CAVs) in particular traffic scenarios [7]. One particular question that still remains unanswered is "how to take advantage of the unprecedented levels of traffic and near-by vehicles information to improve the driver's decision making and performance?"

In this paper we have two main objectives: (1) to summarize recent research efforts related to the design of eco-driving systems; and (2) to discuss potential research directions. We report related efforts in driver feedback-based controls according to the vehicle powertrain configuration, i.e., conventional engine-powered, hybrid and plug-in hybrid and battery electric.

Any such effort has obvious limitations. Space constraints limit the description of the various approaches in detail, and thus, extensive discussions are included only where they are important for understanding the fundamental concepts or explaining significant departures from previous work. In all cases, breadth of perspective and fundamental concepts are emphasized over detailed technical arguments. Note that eco-driving systems provide real-time feedback to the drivers and thus, they need a user-machine interface with easy interpretation of the instructions to minimize driving distraction and assure a safe driving. The study of those interfaces and their level of distraction is thus an additional relevant topic related to eco-driving that is beyond the scope of this work.

The structure of the paper is as follows. In sections II, III and IV, we cover basic definitions and summarize highlights from the literature related to driver impact in conventional, hybrid and plug-in hybrid and battery electric vehicles respectively. In Section V, we present our conclusions and discuss the major opportunities we see for further research.

II. Driver Feedback Systems for Eco-Driving

Recent studies indicate that fuel consumption and emissions can be reduced in existing vehicles by as much as 30% by altering the driver's driving style [1]. One of the most promising approach involves providing immediate information to the driver about the effect of driving behavior on fuel consumption. Driver feedback systems (Fig. 1) provide instructions to drivers aimed at achieving an eco-driving style, or even providing warnings to avoid a

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This work was supported by the Laboratory Directed Research and Development program of the Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA, managed by UT-Battelle, LLC, for the US Department of Energy (DOE), and in part by UT-Battelle, LLC, through DOE contract DE-AC05-00OR22725. This support is gratefully acknowledged.

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potential collision. Feedback for adapting an eco-driving style is typically accomplished by using information from fuel-efficient driving profiles that are obtained through the use of optimization routines. Such information can be provided to the driver either online or offline.

A. General performance metrics in eco-driving

There are specific actions that can help the drivers improve their driving style [8], e.g., accelerate smoothly, try to keep a steady speed, shift up early, etc. Some systems can provide feedback to the driver by following these simple rules [9], [10]. However, to maximize the benefits of eco-driving it is important to know when to apply these rules and how they need to be adapted according to the specific vehicle powertrain configuration.

The objective here is to find an energy-efficient speed profile that reduces energy consumption while ensuring the safety of the driver. The approaches to derive energy efficient speed profiles can be broadly categorized as optimal approaches and heuristic approaches. While most of them can be applied to any type of vehicle, their effectiveness will be maximized if their formulation involves the dynamics of the particular vehicle powertrain configuration [11].

Fig. 1. Example of a visual driver information and feedback display systems.

III. Driver Feedback for Conventional Vehicles

Conventional vehicles are powered only by an internal combustion engine. Their efficiency is very sensitive to the time spent on idling and stop-and-go patterns. There have been research efforts to integrate some degree of traffic information into eco-driving systems aimed at improving the driver's driving style.

A. Optimization-Based Approaches

The optimal control problem aims at minimizing a function that estimates the fuel or energy consumption of the vehicle over a particular trip. This problem is subject to different constraints to ensure drivability, safety and satisfaction of driver power demand. The most common constraints found in the literature include the minimum and maximum speed and acceleration limits and the maximum time allowed for the entire trip.

The optimization problem solved by Wollaeger *et al.* [12], aims at minimizing the engine fuel flow rate as a function of engine torque and speed, this function is commonly found in the form of an engine fuel consumption map, but it can also be defined as a polynomial function with tunable parameters. The authors proposed a two-step optimization process. First the fuel consumption optimization problem is solved with dynamic programming (DP) by using a coarse grid. Then, a finer grid is defined around the initial optimal solution to find the global optimal. Their method, known as "pseudo-dynamic programming," uses traffic information to define the constraints of the optimization problem. This work was later extended by Ozatay *et al.* [13] and tested in real-time using a driver assistant system. Similar approaches were proposed and solved using DP in [14] and [15].

In the research reported in [1] and [16], the authors investigated the driving factors that have a major impact on fuel consumption. The system is integrated with an optimization framework that can be used to optimize a driving style with respect to these driving factors. Then they developed a driver feedback system that can provide instructions to the driver in real time to alter her/his driving style and make it eco-friendlier. The optimization problem is subject to speed or time constraints and is solved by applying sequential quadratic programming.

1) Multi-objective optimization.

Kamal *et al.* [17], [18], [19], proposed an optimization framework for fuel economy improvement and presented some traffic network analysis. In [17] the multi-objective optimization target is to minimize four weighted terms: fuel consumption, acceleration, deviation from an imposed speed limit, and deviation from the desired gap distance from the preceding vehicle. The fuel economy is estimated as a function of speed and acceleration and a model predictive control (MPC) problem is solved by using computation and the generalized minimum residual method. They analyzed the effects of using the proposed system on a road section with intersections controlled by traffic lights using results from a simulation in the traffic simulator AIMSUN [20]. A similar problem was proposed in [19]. In [18], the authors included some information about the upcoming terrain and proposed to optimize the velocity profile by minimizing three terms: the cruising fuel consumption, the acceleration force due to road grade, and the tracking speed error with respect to the driver-desired velocity. Each term is multiplied by a weighting term whose values are tuned through observation. Fuel consumption is estimated by using a polynomial function.

The problem of smoothing the traffic flow by controlling a host vehicle was addressed in [21]. The dynamic behavior of the following vehicle is included in the multi-objective optimization, and the dynamics of the *n* preceding vehicles are used to estimate the future speed trajectory of the host vehicle. The cost function includes four weighted terms: deviation error from desired velocity, host vehicle acceleration, following vehicle acceleration, and deviation error from the desired gap with the preceding vehicle. Through numerical simulation the authors showed that the system is able to reduce the propagation of a traffic jam on uniformly distributed dense traffic.

In [22], [23], the problem of finding optimal trajectories by indirect fuel consumption optimization was addressed. The problem in [22] is formulated, as to minimize velocity transients and trip time, by predicting traffic using a feed-forward traffic estimator based on the gas-kinetic model. DP was used while it was emphasized the importance of prediction accuracy in achieving the potential improvements.

Zhang and Vahidi [24] proposed a predictive cruise control that uses probabilistic prediction of the preceding car position. The optimization problem is formulated to minimize the vehicle's acceleration and the car-following error so that efficiency can be improved while safety requirements are met. The estimation of the probability distribution for the position of the preceding car is made using a Markov chain model, and the problem is solved with MPC. In [25] the cost function for the multi-objective optimization problem includes the probabilistic prediction of the traffic signal timing and it is solved using deterministic DP in a receding horizon way. DP has been also used to solve multi-objective optimization problems in [26], [27], [28], [29], and [30]. Kerper *et al.* [27] used historical data to predict a short-term future velocity profile that is optimized to minimize fuel consumption. The comprehensive modal emission model was used to evaluate fuel and emissions, and a dynamic time warping algorithm was used for clustering.

Wang *et al.* [29] used an emissions map to derive a speed profile that produces minimum emissions and used it as a reference speed. The proposed multi-objective problem includes the cost of deviations from the emissions-optimal speed, the cost of deviation from a desired speed, the cost of deviating from the desired gap with the preceding vehicle, and, finally, the cost of high acceleration values. The problem is solved using DP for uniform prediction time windows. Simulations were performed for a 1 km single lane ring road for two average vehicle densities and assuming all the vehicles are equipped with the system.

B. *Heuristic Approaches*

The research efforts in this section focus on the use of heuristic rules to find velocity profiles that reduced fuel consumption. The approaches in [31], [32], and [33] used signal phasing and timing information to compute ideal and/or feasible velocity profiles. The overall goal is to derive the speed profile to avoid stopping at a red light, whenever possible, and thus reduce idling operation. The signal phase and time can be predicted or assumed to be deterministic. Rakha *et al.* [31] used the velocity profiles as inputs to estimate the required fuel consumption from the Virginia Tech microscopic model. The approach presented by Munoz-Orgarero and Magaña [34] attempts to reduce the use of the brakes when the vehicle is approaching a traffic signal that requires the vehicle to stop. The authors used image recognition algorithms to detect a set of specific traffic signals. Then the distance required to stop the vehicle without using the brakes is calculated and used to advise the driver when to release the accelerator pedal. The rolling resistance and road slope information are used in the speed calculation. Fuel consumption is calculated from the mass air flow sensor and the vehicle speed obtained from the OBD2 port. From the experimental results they concluded that decelerations greater than 1.5 m/s^2 produce an exponential increment in fuel consumption and confirmed that smooth acceleration patterns correlate to reductions in fuel consumption.

Jiménez *et al*. [35] proposed a set of action rules based on the solution derived using DP. The objective is to minimize fuel consumption that is computed using a fuel consumption map in conjunction with the road slope. The proposed feedback system allows real-time advice, accounting for traffic information. Vagg *et al.* [36] used information about the time between peaks and troughs of the speed profile, the acceleration, and the relative positive acceleration, which is a function of position, speed and acceleration, to give feedback to the driver in real time. The feedback includes gear shifting advice.

IV. Driver Feedback for Hybrid and Plug-in Hybrid Vehicles

Hybrid electric vehicles (HEVs) (Fig. 2) and plug-in HEVs (PHEVs) have attracted considerable attention due to their potential for reducing petroleum consumption and greenhouse gas emissions. This capability is mainly attributed to: 1) the potential for downsizing the engine; 2) the capability of recovering energy during braking, and thus recharging the energy storage unit (e.g., battery or ultracapacitor); and 3) the ability to minimize engine operation at speeds and loads where fuel efficiency is low. In addition, hybridization of conventional powertrain systems, which typically refers to the power requirements for the electric motor or the degree of electrification, allows elimination of near-idle engine operation, thus enabling direct fuel economy enhancement.

A typical HEV consists of the fuel converter (internal combustion engine), the inverter, the battery, and the electric machines (motor and generator). HEVs may be categorized, based on architecture, as one of three types: 1) parallel, 2) series, or 3) power split. In parallel HEVs, both the engine and the motor are connected to the transmission, and thus, they can power the vehicle either separately or in combination. The series HEV, in which the electric motor is the only means of providing the power demanded by the driver, is the simplest HEV configuration. Finally, the power split HEV can operate either as a parallel or a series HEV, combining the advantages of both. PHEVs are hybrid vehicles with rechargeable batteries that can be restored to full charge by connecting a plug to an external electric wall socket. A PHEV shares the characteristics of both an HEV, having an electric motor and an internal combustion engine, and an all-electric vehicle (EV), having a plug to connect to the electrical grid. This is especially appealing in situations where daily commuting is within a small amount of miles. These vehicle architectures usually have regeneration capabilities, which allow them to be more efficient in transient operation. Attempts to develop eco-driving systems for these HEV architectures frequently involve in-vehicle optimization.

A. *Optimization-Based Approaches*

Bouvier *et al* [11] considered two approaches to find the optimal speed profile. In the first approach, they used general terms that play an important role for a conventional engine powered vehicle: the fuel consumption, the total travel time and a penalty term that penalizes the speed values above the stated limits. In the second approach, the authors included a fourth term related to the battery State of Charge (SOC) into the cost function. They implemented an optimal energy management strategy for the HEV and compared the fuel consumption results using the two optimal speed profiles. They found that considering the specific powertrain configuration when computing the optimal speed profile, can further increase the fuel economy by 2% to 3% percent. Other optimization-based approaches can be found in [37] and [38]. Mensing *et al.* [37] proposed to use DP to find the optimal velocity trajectory by minimizing the fuel consumption, state-of-charge variation rate, and time.

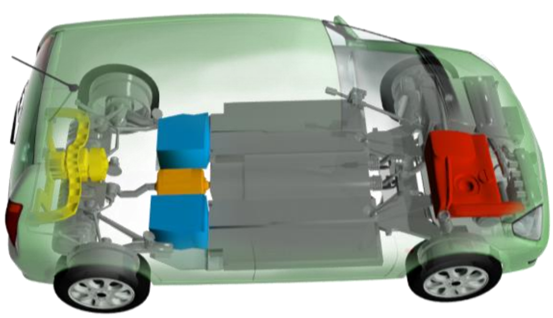

Fig. 2. HEV configuration showing the engine (red), the inverter (orange), the battery packages (blue), and the electric machines (yellow).

B. *Heuristic Approaches*

Calculating optimal deceleration patterns that maximize the energy recuperation along a route is the focus of Van Keulen *et al.* [39]. Using vehicle mass and geographical information to take advantage of road elevations, they predict the velocity profile for a particular route. Then, they compute the required deceleration that allows the electric machine to generate at its maximum value and avoid the use of the mechanical brakes. The predicted speed profile is used later to find the optimal controls for in-vehicle energy management. Van Keulen *et al.* [40] and Vajedi *et al.* [41] proposed to divide the route into segments and to define a particular optimal trajectory shape for each segment. Then nonlinear programming is used to find the parameters for each segment that minimizes fuel consumption.

V. Driver Feedback for Electric Vehicles

EVs are powered by an electric motor and a battery. The range or maximum number of miles the vehicle can travel without recharging is an important characteristic defining vehicle performance. The main goal of eco-driving systems for all-electric vehicles is to reduce the battery energy consumption such that the vehicle range is increased.

Energy consumption optimization is the focus of two studies reported in the literature recently [42], [43]. Employing heuristic rules in [42], the authors investigated the feasible time ranges that allows a vehicle to pass through traffic lights without stopping and using this time windows, they divided the optimization problem into sub-problems that are solved to find the sub-optimal speed profile. In [43], the authors presented a macroscopic steady-state analysis of an urban traffic network subject to boundary flows affected by traffic lights and variable speed limits. The cell transmission model, adapted to urban traffic, is used to model the system and it is assumed that the vehicles on the road travel at an equilibrium speed. Thus, the road section is divided into homogeneous cells to represent the traffic flow. In this particular study, there are two representative cells: the congested cell and the free cell. The authors solved a multi-objective optimization problem to select the optimal velocity of the free cell using the instantaneous travel time, total travel time, total travel distance, and energy at the macroscopic level as the parameters of the cost function. Through the simulation of a road section with two traffic lights it was shown that the problem has a nontrivial solution.

Wang *et al.* [44] investigated the problem of optimally controlling how to accelerate and decelerate a non-ideal energy-aware electric vehicle so as to (a) maximize its cruising range and (b) minimize the traveling time to a specified destination under a limited battery constraint. Although the proposed solution for the cruising range maximization problem can be attained numerically, the authors proposed an approximate solution structure that the original optimal control problem can be transformed into a simpler nonlinear parametric optimization problem. Using this methodology to the travelling time it can yield practically realizable results.

Freuer and Reuss [45] used predictive route data and information from a radar sensor to optimize energy use by minimizing the electric powertrain losses. The optimization problem is solved online using DP for time horizons of different lengths depending on the available predictive data. Similar approaches, with focus on the minimization of energy losses, were proposed by Dib *et al.* [46] and Tan *et al.* [47]. A multi-objective optimization problem that penalizes energy consumption, travel time and driving comfort is proposed in [48]. The optimal velocity profile is computed offline and used to provide feedback to drivers while driving an electric vehicle on an actual highway.

The optimization framework proposed in [1] for conventional vehicles was used to implement a driver feedback system for an electric bus in [49]. In this work, the optimal problem involves the minimization of the instantaneous vehicle power consumption that is modeled as a function of the speed and acceleration. Given the dimensions of the vehicle, the grade has a non-negligible impact on the vehicle power request. Thus, it is included in the instantaneous power meta-model which was generated by using experimental data from a real battery electric bus. In addition, the authors proposed a driver feedback interface and a driver scoring method to allow the driver improving the driving skills.

Wu *et al.* [50] proposed an approach that assumes that information regarding the upcoming terrain and real time traffic data is available and consider the queues at intersection crossings. The optimization problem aims at minimizing the vehicle energy consumption, which is a function of speed, acceleration and road grade, subject to state constraints, queue limitation, travel time limits and states boundaries.

More recently, Yi and Bauer [51], considered the weather conditions, specifically the wind speed, into the optimization problem. The proposed optimization problem aims at minimizing the aerodynamic and rolling resistance energy losses of the vehicle.

VI. Driver Feedback for Eco-Driving: Summary

Most of the driver feedback systems address the issue of finding an optimal speed profile in terms of fuel/energy consumption for a single vehicle. When attempting to account for traffic in the formulation, traffic lights and car following have been extensively studied while limited consideration has been given to ramps, intersections, or lane changing. The majority of the papers predict, or assume that some sort of traffic information is available, and use it to set constraints for the optimization problem. DP is the most frequently used strategy, but some authors have also used MPC, and non-linear programming. The most commonly used software tool is Matlab/Simulink, followed by AIMSUN, PSAT, and Autonomie. In HEVs, it is common to have a two-level optimization. Typically, in the first level the speed profile is optimized and in the second level, there is in-vehicle optimization to achieve further improvements. In the case of electric vehicles, the approaches are similar to the case of conventional vehicles, but instead of minimizing fuel consumption, the goal is to minimize the energy consumption.

Table 1 categorizes the references according to the type of solution, i.e., optimization or heuristics, the method of evaluation, i.e., simulation or field test, and the percentage of fuel, energy, and equivalent fuel consumption improvement. While some optimization-based approaches can yield more than 20% improvement in fuel or energy consumption, they are not always amenable to real time implementation and most of the reported results are based on simulations.

VII. Driver Feedback for Safety

A significant amount of research has focused on developing information systems for improving safety such as vehicle collision warning systems (CWSs). CWSs provide warning signals to alert the driver when potential collisions are detected. Typical CWSs are based on the information obtained by the vehicle using radar and acoustic and vision sensors. The sensors yield relative information about the vehicle and moving or stationary obstacles. This information is then processed to determine the likelihood of a collision and to estimate the time to collision. A warning is issued if the estimated time to collision is smaller than the specific threshold under the specific scenario. Tan and Huang [52] explored the engineering feasibility of a cooperative CWS (CCWS) where vehicles are equipped with a differential global positioning system and basic motion sensors. The paper provided a comprehensive exploration of possible functional architectures for such systems and presented an example demonstrating the engineering feasibility of such designs. Car-to-car overlay networks for enhancing safety in a group of cars has also been investigated for CCWSs (Aoyama and Takeichi [53]).

Advanced driver-assistance systems (ADASs) provide essential information to the driver aimed at automating difficult or repetitive tasks and thus can lead to an overall increase in safety and an enhanced driving experience. Ammoun *et al.* [54] investigated the contribution of intervehicle communication (IVC) in ADASs and compared it with traditional safety sensors. Tampere *et al.* [55] presented a continuous human-kinetic traffic-flow model for the explorative analysis of ADASs. It is a multiclass variant of kinetic traffic-flow models that is strongly based on individual driver behavior, i.e., on fully continuous acceleration/deceleration behavior and explicit modeling of the activation level of the driver. The effectiveness of its efficiency was illustrated on a queue tail warning ADAS that alerts drivers when approaching sudden decelerations in queue tails.

Slowdown warning systems aim to simultaneously provide information to all drivers in a platoon of vehicles when a vehicle abruptly decelerates. This advance information gives the drivers more time to react in preparation for the impending slowdown, and as a result, it increases the distances between vehicles. Chakravarthy *et al.* [56] investigated scenarios aimed at providing advance warnings to enhance safety in the context of IVC. They looked at various scenarios wherein only a subset of the vehicles in a multivehicle stream was equipped with advance-warning capabilities. In their study, it was shown that conditions exist wherein even equipping some of the vehicles with such systems can be sufficient to alleviate crashes, including in the unequipped vehicles. Chiara *et al.* [57] investigated the use of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication systems to reduce secondary accidents whose occurrence is often due to low visibility and/or poor weather conditions where conventional safety features/systems such as brake lights are not effective. A case study of five vehicles traveling in a single lane was used to estimate the effect of V2V and V2I communication systems on reducing secondary accidents. The results and explanations show that the use of such systems may be an efficient way to reduce the number of secondary accidents. Torrent-Moreno *et al.* [58] analyzed V2V communication from an active-safety perspective and identified the challenges and associated strategies for improving performance through packet-level interference management. In this context, they proposed a distributed transmission power control strategy that allows the bandwidth to be made available for higher priority data like dissemination of warnings.

Systems based on trends of cooperative driving have been proposed that enable an electronic safety horizon for foresighted driving by implementing onboard vehicle hazard detection and V2V communication [59]. These systems can focus on low penetration levels in rural traffic through a message-management strategy that is based on storing warning information in the vehicle and distributing warnings through communication, particularly with oncoming traffic. They can also provide timely warnings to drivers concerning dangerous situations ahead by decentralized distribution of warnings and incident messages via heuristic IVC. Gomes *et al.* [60] proposed a cooperative driver-assistance system that leverages V2V communication to transform vision-obstructing vehicles into transparent tubular objects. The system combines several technologies that are available in modern vehicles such as windshield cameras, computer vision, and laser holographic projection. Umedu *et al.* [61] proposed an IVC protocol aimed at detecting drivers who violate the speed limit. In their approach, each vehicle communicates identification information on surrounding vehicles with other vehicles and propagates warning information that is then forwarded using ad hoc communications. Garcia-Costa *et al.* [62] developed a stochastic model that yields the probability of collisions in a chain of vehicles where a CWS is available. The inherent assumption is that due to the existence of the warning notification system all drivers react to the warning message independently, and thus the motion equations can be simplified. The model is independent of the particular communication system used as long as its operation can be characterized by an appropriate notification delay including communication latency and driver reaction time.

The references related to driver feedback systems for safety are also categorized in Table I according to the method used for validation.

VIII. Concluding Remarks and Future Direction

Based on the studies summarized here, it appears that most of the research in eco-driving to date has focused on conventional vehicles but some recent work has begun to address hybrid electric and battery electric vehicles. Given the differences between internal combustion engines and electric machines, speed trajectories that are optimal for conventional vehicles are not necessarily optimal for HEV or electric powertrains. Furthermore, given the different aerodynamics of light- and heavy-duty vehicles, optimal speed trajectories for them are not necessarily the same either. In general, DP and MPC seem to be the preferred tools for performance optimization.

Table I. Summary of results for driver feedback approaches.

Category	**Energy/Fuel/Equivalent Fuel Consumption Improvement**				
	<10%	**10% to 20%**	**20% to 30%**	**>30%**	**Not Stated or N/A**
Optimization	[17],[18], [27],[29], [45],[51]	[11],[12], [13],[14], [19],[25], [30],[37], [46]	[1],[15], [16],[22], [43]	[23],[24], [47],[49], [50]	[21],[26], [28],[44], [48]
Heuristic	[35],[36], [40]	[32],[39], [41],[63]			[31],[33], [34],[42]
Evaluated through Simulation	[17],[18], [27],[29], [51]	[11],[12], [14],[19], [25],[32], [37],[39], [41]	[1],[15], [16],[22], [43]	[23],[24], [47],[49], [50]	[21],[26], [28],[31], [33],[42], [55],[56], [57],[58], [60],[61], [62]
Evaluated through Field Test	[35],[36], [40],[45]	[13],[30], [46], [63]			[34],[44], [48],[52], [54],[55], [59]

Most of the published work focuses on finding an optimal velocity profile for a single vehicle by solving similar optimization problems and adding or neglecting particular parameters. Furthermore, the main assumption in most cases is that the vehicle speed is only limited by pre-established speed limits and just a few authors have considered the speed limitations imposed by the traffic. Thus, following the suggested optimal patterns in real world traffic can have negative impacts in the energy efficiency and safety of eco-driving approaches. More recently, some research efforts have started exploring the overall effects of eco-driving systems on traffic networks and the possibilities of creating eco-driving systems for a fleet of vehicles or an entire vehicular network. The objective is to find a speed trajectory that avoids collision and minimizes travel time. This new trend may lead to significant contributions to the sustainability of the entire transportation infrastructure.

As the necessity for CAVs is becoming pervasive, it seems that driver feedback systems could be potentially combined with CAVs and provide solutions for improving both safety and efficiency for the entire transportation network. It is apparent that new approaches are needed that can take advantage of external information collected in real time, to maximize the benefits of eco-driving systems. The advent of CAVs provides the opportunity for such new approaches as they foster the development of improved systems to monitor traffic conditions and the design and implementation of optimal strategies as a result of the available global data and information. However, many challenges have still to be addressed before having a massive deployment of fully automated vehicles. It is expected, that CAVs will penetrate in the market slowly and interact with non-autonomous vehicles.

Two critical questions need to be addressed: 1) how to take advantage of the connected environment and driver assistant systems to provide instructions to drivers? and 2) how to account for the uncertainty produced by drivers who do not follow the instructions to guarantee the safety of the traffic network? Investigating methods to habilitate autonomous and non-autonomous connected vehicles to safely interact under realistic scenarios is critical to fully exploit the opportunities to improve efficiency and reduce emissions, offered by intelligent transportation systems. Furthermore, driver responses to external information related to real-time conditions, social and news media can have a significant impact in the traffic network efficiency and safety and thus, it is imperative that eco-driving systems involve some level of driver behavior prediction.

Given the previous extensive research into how best to link human controllers with other complex systems such as nuclear reactors and aircraft [64], [65], and [66], it would seem prudent to consider how results from those studies might apply to the present context. We suggest that, given the current state of the art, there are many opportunities to improve the basic understanding of how real-time information, drivers-in-the-loop and the driver-vehicle interface can be optimally integrated. We also expect that the most impactful results will be integrated by studies that bridge across multiple traditional disciplines, such as mathematics, computational simulation, statistics, mechanical and electrical engineering, measurement science, neuroscience and human factors engineering.

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