CONNECTED VEHICLES AND POWERTRAIN

OPTIMIZATION

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FIGURE 1 Michigan Tech NEXTCAR project.

Connected and Automated Vehicles (CAV) are emerging technologies that have a great potential to improve the safety, mobility, and energy efficiency of transportation systems. The U.S. Department of Transportation (DOT) and Department of Energy (DOE) have supported the research and development of CAV technologies in recent years to demonstrate the benefits of CAV technologies in real-world transportation systems. The authors of this article have participated in Michigan Technological University (Michigan Tech) NEXTCAR project funded by the DOE Advanced Research Projects Agency-Energy (ARPA-E). This article consists of three parts. First, the basic concept of CAV technology and the common methods to improve fuel economy are introduced. The effects of connectivity on vehicle/powertrain control and optimization are then discussed. Finally, Michigan Tech NEXTCAR project is presented to provide a more detailed view of predictive vehicle/powertrain control enabled by CAV technologies.

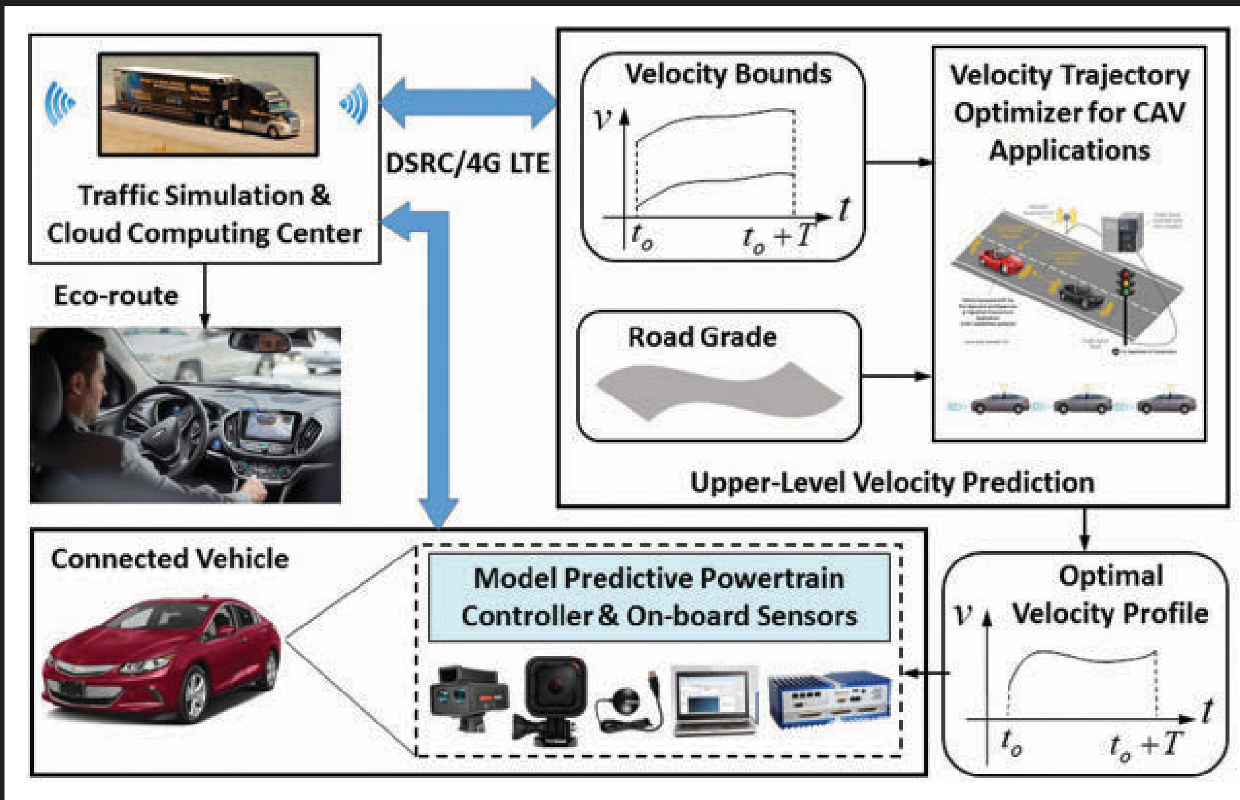

FIGURE 2 Predictive powertrain control enabled by CAV technologies.

CONNECTED AND AUTOMATED VEHICLE TECHNOLOGY

Connected and automated vehicles are potentially paradigm-shifting technologies for the improvement of safety, mobility, and efficiency of transportation systems. Connected vehicles and automated vehicles are two different technologies. Connected Vehicles (CV) are able to communicate with nearby vehicles and roadway infrastructure through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications. The V2V and V2I communications use wireless technology, such as Dedicated Short Range Communications (DSRC) [1] or cellular network (e.g., 4G/LTE). For Automated Vehicles (AV), the U.S. Department of Transportation (DOT) defines AVs as [2] "those in which at least some aspect of a safety-critical control function (e.g., steering, throttle, or braking) occurs without direct driver input." Based on the level of automation, the Society of Automotive Engineers (SAE) standard J3016 [3] defines six levels of driving automation: L0-No Automation, L1-Driver Assistance, L2-Partial Automation, L3-Conditional Automation, L4-High Automation, and L5-Full Automation. L1 vehicles only have one automated control function (either steering or acceleration/deceleration) and L2 vehicles have two automated control functions (both steering and acceleration/deceleration). There is a key distinction between L2 and L3. For the levels below L2, a human driver performs part of the dynamic driving task while for L3 or above, an automated driving system performs the entire dynamic driving task. L3 and L4 vehicles are capable of automated driving only for some driving modes, and L5 vehicles work for all the driving modes. The difference between L3 and L4 vehicles is that L3 vehicles expect that a human driver will take over full control if it is required, but L4 vehicles work reliably even if a human driver does not respond appropriately to a request for intervening.

The U.S. Department of Transportation (DOT) and other federal/state funding agencies have supported research and pilot deployment efforts to develop crosscutting CV technologies and evaluate the effectiveness of CV technologies in real-world transportation systems. One recent DOT award has been made to New York City Department of Transportation (NY DOT), Tampa Hillsborough Expressway Authority, and Wyoming Department of Transportation (Wyoming DOT) to pilot next-generation connected vehicle technology [4]. The NY DOT pilot installs V2V technology in up to 8,000 city-owned vehicles that frequently travel in Midtown Manhattan, as well as upgrades traffic signals and roadside units with V2I technology. The pilot in Tampa provides peak rush-hour congestion solutions and protects pedestrians by using smartphone communication between pedestrians and vehicles. The Wyoming DOT project focuses on the efficient and safe movement of freight through the I-80 east-west corridor. By using V2V and V2I, the Wyoming DOT project will collect real-time traffic information and disseminate to vehicles that are not equipped with the new technologies.

The concurrent development of connected and automated vehicle technologies is anticipated to provide synergistic benefits [4] to improve traffic safety, mobility, and energy efficiency [5]. For vehicle fuel economy, the major factors that increase vehicle fuel consumption are rapid acceleration/deceleration, number of stops, traffic congestion, and bad road conditions. CAV technologies are being investigated to properly control these factors to reduce fuel consumption [6, 7], including Eco-routing [8], Speed Harmonization (SPD-HARM) [9], Eco-Approach and Departure (Eco-A/D) [10, 11], Platooning [12], and Cooperative Adaptive Cruise Control (CACC) [13].

Eco-routing strategy selects routes with the objective of minimizing fuel consumption or emissions, as opposed to the traditional objective of minimizing travel times [8]. Speed harmonization is a method to reduce temporal and spatial variations of traffic speed to reduce congestion and improve traffic performance [9]. The Eco-A/D approach aims to eliminate stop/start or achieve most efficient deceleration/acceleration at signalized intersections. In Eco-A/D applications, Roadside Equipment (RSE) units at intersections broadcast Signal Phasing and Timing (SPaT) information and intersection geometry information to approaching vehicles [10]. Upon receiving this information, the Eco-A/D algorithm determines the vehicle's optimal speed profile to pass through the intersection on a green light or to decelerate to a stop and launch the vehicle in the most eco-friendly manner [14, 15].

Platooning and CACC are cooperative CAV technologies for a platoon of vehicles to improve safety and throughput [16]. Both platooning and CACC are composed of a lead vehicle and several close-following vehicles through cooperative driving enabled by V2V communication. However, there are two differences between platooning and CACC [17]. First, platooning is capable of both lateral and longitudinal control while CACC only provides longitudinal control. Second, the platooning system applies Constant Distance Gap (CDG) control strategy while CACC employs Constant-Time Gap (CTG) control strategy; the distance between vehicles in CACC systems is proportional to the speed [17]. The lead vehicle of a platoon communicates with the followers to provide its instantaneous location, speed, and acceleration, which allows the followers to follow the leader safely with smaller inter-vehicle spacing. The cooperative driving of platooning/CACC enables a string of vehicles to reduce their combined aerodynamic drag and reduce the total fuel consumption of the cohort of vehicles.

EFFECTS OF CONNECTIVITY ON VEHICLE/POWERTRAIN CONTROL

Predictive Control

Connectivity makes increased real-time information available on-board in the vehicle through V2V and V2I communications. This useful information includes traffic and environmental conditions, topography, road surface conditions, and surrounding vehicles [18]. Synthesis of this information allows vehicle/powertrain control to be predictive and forward-looking. For example, a connected vehicle knows future power demand based on traffic and road conditions received from V2I communication. Given future power demand, the most efficient powertrain control law can be found through model predictive control. This is especially useful for complicated powertrains such as a multi-mode hybrid powertrain consisting of multiple energy/power sources and sinks. In Eco-A/D applications, both V2I and V2V communications can be used for CAVs to collect traffic flow and traffic light data at intersections, and nearby vehicle operation information to generate optimal profiles of acceleration/deceleration and braking/regeneration to go through the intersection during the green phase of the light. The optimized longitudinal vehicle control and powertrain control can reduce fuel consumption by avoiding unnecessary stops.

Cooperative Control

Advancement in connectivity and automation also allows CAVs to cooperate with surrounding vehicles in platooning and CACC driving modes. Cooperative driving is a promising driving pattern to significantly improve transportation efficiency and reduce fuel consumption by utilizing information exchange among vehicles in addition to on-board sensor measurements. However, cooperative driving is vulnerable to unreliable vehicular communications such as packet loss and transmission delay when vehicular kinetic information or control commands are disseminated among vehicles [19]. If wireless communication fails, CACC would automatically degrade to conventional Adaptive Cruise Control (ACC), leading to a significant increase in minimal time headway to maintain string-stable behavior [20]. Tradeoffs between CACC performance and network specifications need to be made to achieve desired overall control performance under network constraints [21]. Due to the nature of cooperative driving in platooning/CACC, control approaches such as consensus control and distributed multi-agent coordination have been investigated from a networked control system perspective [12, 19, 22]. The major factors in platooning/CACC control systems include vehicle dynamics, the information to be exchanged among vehicles, the communication topology describing the connectivity structure of vehicular networks, and the control law to be implemented on each vehicle in order to define the car-following rule [19].

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Darrell Robinette, PhD, P.E. is an assistant professor in the department of Mechanical Engineering-Engineering Mechanics. Darrell joined Michigan Tech in August of 2016 after a nine-year career at General Motors where he served in a variety of roles. Dr. Robinette's career at GM started in 2007 as a powertrain integration engineer at the Noise and Vibration Center at the Milford proving grounds working as a specialist in drivetrain torsional dynamics. In 2011, Dr. Robinette transferred to the automatic transmission Road-to-Lab-to-Math group developing methodologies for implementing model-based control algorithms and dynamometer-based calibration techniques into production vehicle programs with the aim of increased efficiency and robustness with respect to drive quality. In late 2015 Dr. Robinette transitioned to the electrification propulsion systems engineering group working on a range of topics related to system dynamics for the next generation of electrified propulsion systems.

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Jeremy Worm joined APS LABS in 2007. Mr. Worm is the Director of the Michigan Tech Mobile Lab. Mr. Worm is active in research and testing projects in the areas of engines, alternative fuels, combustion, emissions, and vehicle systems. Worm has developed and previously taught two courses in Hybrid Electric Vehicles, and has developed and currently teaches a course in Powertrain and Vehicle Instrumentation and Testing. Prior to joining APS LABS, Mr. Worm was a Senior Engineer at GM Powertrain working on a variety of engine development projects. Mr. Worm holds an MS in Mechanical Engineering, is working on a PhD in Mechanical Engineering, and is a Licensed Professional Engineer.

Chris Morgan has worked for over 7 years in HEV and EV system design, integration, and execution of electrified vehicles. Chris was a calibration engineer at General Motors, specializing in electric machine and power electronic diagnostics. Additionally, Chris spent time working as an algorithm and software development engineer in hybrid controls, including engine start/stop and P1 HEV algorithms. Chris also spent time as a development and validation engineer in electrified drive systems, and was a diagnostic strategist for the Chevy Bolt program.

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Integrated Vehicle Dynamics and Powertrain Control

Conventional powertrain control is mostly reactive to current driving information. With V2V and V2I communications, look-ahead trip data will be made available to on-board vehicle/powertrain controllers. This will allow an integrated vehicle-level dynamics and powertrain control to achieve better fuel economy. The ARPA-E NEXT-Generation Energy Technologies for Connected and Automated on-Road Vehicles (NEXT-CAR) Program recently funded 10 awards for the development of new vehicle dynamics and powertrain (VD&PT) control technologies [23]. The overall objective of the NEXTCAR Program is to develop optimized and coordinated VD&PT control technologies that improve the energy efficiency of connected and automated vehicles. The program promotes collaboration among vehicle dynamics control, transportation analytics and powertrain control engineers to formulate solutions that use real-time information available via connectivity for the vehicle operation either in isolation or in cooperation with nearby vehicles.

MICHIGAN TECH NEXTCAR PROJECT:

Connected and Automated Control for Vehicle Dynamics and Powertrain Operation on a Light-Duty Multi-Mode Hybrid Electric Vehicle

With funding from the ARPA-E NEXTCAR program, Michigan Tech in collaboration with GM is developing and demonstrating the benefit of CAV technologies and powertrain optimization using a fleet of eight 2017 Chevrolet Volts and a Mobile Lab (ML). The ML hosts a connected and automated vehicular traffic simulation platform, which provides optimal eco-route and velocity bounds to a vehicle dynamics and powertrain model/controller for a range of CAV applications. The model-based predictive controller (MPC) encompasses a real-time VD&PT dynamic model leveraging vehicle connectivity (V2X) with real-time traffic modeling and predictive speed horizons and eco-routing. The objective is to achieve 20% reduction in energy consumption (electric + fuel) through the real-time implementation and connection of CAV control strategies and powertrain energy management MPC algorithms. Connectivity data from vehicles, infrastructure, and cloud server combined with a dynamic model of the vehicle powertrain system allow the prediction of the vehicle's future speed profile and enable forward-looking optimization of powertrain mode selection, energy utilization from the battery and fuel source, and distribution of propulsive torque from the electric motors and/or internal combustion engine. Development and testing will be performed with a completely integrated vehicle and traffic simulation model.

Michigan Tech ML is used as the control center, vehicle to cloud communication hub, coordinated vehicle center, and mobile charging station for the fleet of modified Gen2 Volts as shown in **Figure 1**. The ML serves as a mobile computing center in this program to enable real-time traffic simulation, eco-routing, and V2V and V2I communication. The selected vehicle, the Gen2 MY17 Volt, contains unique powertrain architecture that can operate as Electric Vehicle (EV), Hybrid Electric Vehicle (HEV), and Plug-in Hybrid Electric Vehicle (PHEV). The vehicle enables five distinct operating modes, including one-motor EV mode (EV I), two-motor EV mode (EV II), Low Extended Range (LER) mode, Fixed Ratio Extended Range (FER) mode, and High Extended Range (HER) mode. The project conducts research to 1) understand the effects of all major powertrain/vehicle dynamics on the transient performance of connected EVs/PHEVs/HEVs, 2) design and implement real-time mode selection and MPC torque split control strategies that incorporate transient characteristics of the vehicle powertrain (engine, clutches, e-motors, etc.) for connected EVs/PHEVs/HEVs, and 3) develop multi-scale (EV, PHEV, HEV) VD&PT control strategies in platooning/CACC and Eco-A/D applications with different CAV technology penetration rates.

The model-based VD&PT predictive powertrain control system is designed as shown in **Figure 2.** The control system utilizes the information provided by the vehicle connectivity and incorporates vehicle/powertrain dynamics for making the control decisions on vehicle operating mode selection and powertrain energy management to split power among two motors and the IC engine. The control system has three basic control/optimization objectives: 1) optimization of vehicle velocity and power trajectory, 2) energy optimization algorithm to select vehicle operating mode, and 3) model predictive control for optimal powertrain energy management. The control system consists of two layers. The upper layer determines optimal vehicle velocity and power trajectory based on speed bounds from real-time traffic simulation, road grade, V2V/V2I data, and the current state of vehicle/powertrain dynamics. Different from the optimal reference speed profile purely generated from traffic simulation, this layer of optimization considers the fuel/energy penalty associated with vehicle/powertrain dynamics and powertrain physical constraints. The optimization algorithm calculates the optimal vehicle velocity trajectory that minimizes the energy/fuel consumption for the next prediction horizon. Then, the projected torque/power request for the vehicle is determined using the projected velocity trajectory and forecasted road grade.

The model predictive powertrain control and energy efficient model selection are implemented in the second layer. The MPC controller for real-time powertrain control incorporates full system dynamics and transient behavior of engine, drive unit, mode switching, electric machines, power inverter and battery. It manages powertrain energy distribution to achieve desired vehicle velocity within the prediction window while maximizing fuel economy and satisfying physical and drivability constraints. The MPC controller solves optimal control actions, the optimal operation mode and required power/torque from engine and two motors, for the control horizon to achieve desired vehicle velocity and torque request derived by the velocity optimizer at the end of the prediction window while maximizing fuel economy and satisfying physical constraints. The optimization cost function is designed to track reference velocity profile and minimize energy consumption. The energy cost includes energy consumed by the engine and electric motors. The electrical energy is converted to an equivalent fuel consumption by an equivalence factor considering the efficiencies of battery, charger and electric motors. The energy cost function also incorporates dynamic fuel penalty, which reflects the impact of vehicle/powertrain dynamics and mode switching. To reduce the dynamics caused by control actions, the cost function also minimizes the change rate of control inputs. The integration of this two-layer control enables powertrain optimization that incorporates information on traffic, infrastructure, and road conditions.

CONCLUSION

Increased CAV technologies are being deployed in real-world transportation systems. This article provides an overview of the impact of CAV technologies on vehicle/powertrain control and highlights that the rich information provided by connectivity and the capability of on-board intelligent control are shifting reactive and isolated vehicle/powertrain control to predictive, cooperative, and integrated vehicle dynamics and powertrain control. ■

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