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Autonomous Eco-Driving Evaluation of an Electric Vehicle on a Chassis Dynamometer

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Abstract

Connected and Automated Vehicles (CAV) provide new prospects for energy-efficient driving due to their improved information accessibility, enhanced processing capacity, and precise control. The idea of the Eco-Driving (ED) control problem is to perform energy-efficient speed planning for a connected and automated vehicle using data obtained from high-resolution maps and Vehicle-to-Everything (V2X) communication. With the recent goal of commercialization of autonomous vehicle technology, more research has been done to the investigation of autonomous eco-driving control. Previous research for autonomous eco-driving control has shown that energy efficiency improvements can be achieved by using optimization techniques. Most of these studies are conducted through simulations, but many more physical vehicle integrated test application studies are needed. This paper addresses this research gap by highlighting the Vehicle Hardware-In-the-Loop (VHIL) energy saving potential of autonomous eco-driving control for connected and automated vehicles. A comprehensive system description of autonomous eco-driving control is presented by describing subsystems and their functionalities. Validated autonomous eco-driving optimization methods, including Dynamic Programming (DP), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) were tested with a control-enabled electric Kia Soul using a 2-wheel-drive chassis dynamometer. VHIL test performance of these methods is evaluated relative to each other as well as a baseline scenario. The conclusions were derived from examinations that were carried out on a chassis dynamometer. The results show that energy efficiency may be enhanced by anywhere from 5 to 15 %, depending on the method that is used. When compared to our earlier simulation results, it is demonstrated that the VHIL outcomes achieve the predicted gain in energy efficiency. The overall results show that the use of the dynamic programming method is the most effective strategy for enhancing energy efficiency. It is shown that the application of methods that are derived from genetic algorithms has the potential to increase energy efficiency when integrated in the test vehicle.

Introduction

In the past decades, in response to growing environmental and economic concerns, policymakers have begun investing in clean vehicle technology, R&D, demonstrations, and deployment efforts. In the United States, the Environmental Protection Agency (EPA) has been concentrating on improving fuel efficiency, decreasing regulated criteria emissions like Nitrogen oxides (NO_x) and particulate matter (PM), and decreasing greenhouse gas emissions by developing cutting-edge vehicle engine and drivetrain technologies[1, 2, 3, 4]. Since electric motors (EMs) are more energy efficient and produce no exhaust emissions, they have been the focus of recent R&D as a potential solution to the aforementioned problems[5, 6, 7, 8]. Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs) are the three main types of electric vehicle (EV) technologies that have been the subject of the research in the past years [9, 10, 11]. The U.S. Department of Energy (DOE) has also been supporting research and development on vehicular electrification by recently announcing a $96 million funding opportunity to assist with the decarbonization of the domestic transportation sector [12].

While the use of alternative fuels, electrified vehicles, and the transition to renewable energy sources are promising, long-term solutions to the aforementioned environmental issues, reducing the emissions of the current vehicle fleet as much as possible is a promising short- and medium-term alternative [13]. Eco-driving (ED) is the control technology of energy-saving driving (such as an energy management strategy), which is accomplished by optimizing the operating point of the engine and/or electric motors at the level of vehicle control algorithms, as defined by extensive research into autonomous driving technology. This study focuses on the integration of automated ED rather than eco-driving which focuses on the driver. Manual ED is susceptible to incorrect acceleration and deceleration events, such as accelerating too quickly or hitting the brakes too violently. This can be caused by a number of factors, including the behavior of vehicles in the immediate area, the stress associated with trying to get somewhere quickly, and the amount of power and torque that is available to the vehicle [14, 15, 16].

The combination of connectivity, automation, and electrification results in a more efficient transportation system and a cleaner environment. Connected and automated vehicles (CAVs) are more accurate than human drivers when it comes to following optimal trajectories and considering information outside their line of sight. Therefore, it is preferable to use technologies to improve the performance of BEVs via ED characteristics. This will increase the energy efficiency, range, and market penetration of electric vehicles. There has been a great deal of research on ED applications, particularly those that improve vehicle safety and energy efficiency [17, 18, 19, 20, 21]. Figure 1 visualizes conceptual CAVs employing multiple sensors and V2X technology.

When designing and implementing an autonomous ED system, the method by which an ED algorithm generates the vehicle's path will have a significant impact on the algorithm's performance. In recent years, a lot of research has been conducted on autonomous ED controls, and several approaches for generating an optimal ED trace have been presented and reviewed separately. The advantage of this study is its consideration of real-time implementable strategies. Rules-Based Eco-Driving, Uniformly Discrete Trajectory Optimization, and Spline Trajectory Optimization are the three primary classifications available in the literature: Rules-Based Eco-Driving (RBED), Uniformly Discretized Trajectory Optimization (UDTO), and Spline Trajectory Optimization (STO). A common RBED algorithm is the Intelligent Driver

FIGURE 1 An image showing how multiple sensors and V2X technology could be used in CAVs [17].

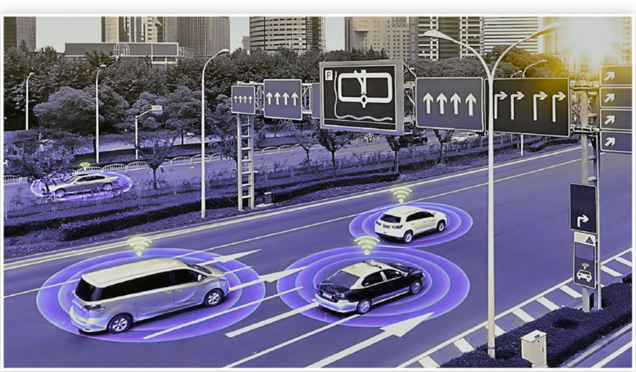
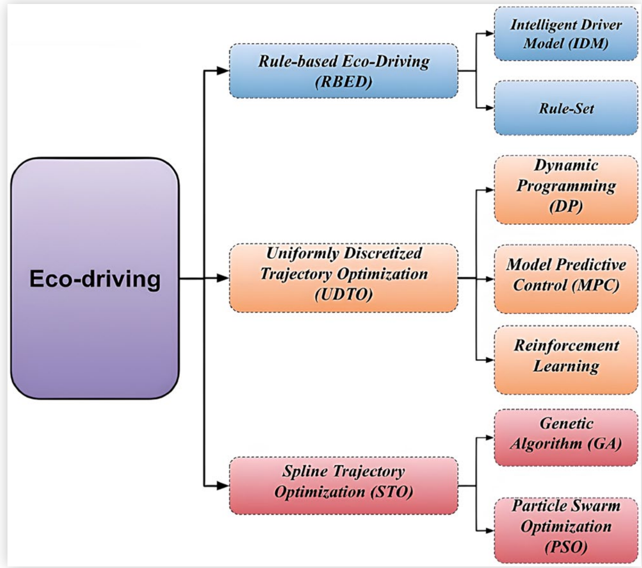


FIGURE 2 The overall framework of eco-driving.



Model (IDM) [23], with several works presenting modified versions of the method in ED simulations. IDM and its derivatives dominate the RBED literature and are often used as a baseline to compare against in the optimal ED literature. Another common technique is the rule-set method. In the surveyed studies, rule-set ED mainly consists of an operation mode control strategy and a fuzzy logic control strategy. Uniformly discretized Trajectory Optimization (UDTO) and Spline Trajectory Optimization methods(STO) are among the most commonly used optimization algorithms for ED. The overall framework of ED is visualized in Figure 2.

According to what was surveyed, there has been a significant amount of study with simulation. However, there is only a limited amount of test data accessible from the relevant literature to evaluate the ED capabilities of autonomous BEVs in Vehicle Hardware-In-the-Loop (VHIL) circumstances. It is unknown how effective autonomous ED for BEVs will be in decreasing fuel consumption when integrated in a vehicle or under what conditions it will function at its best because the technology is still in its infancy and not yet available for commercial use. In order to effectively build, integrate, and calibrate the ED control system, automobile manufacturers need to have a solid understanding of the repercussions and limitations of automated ED in VHIL driving scenarios. This may help raise customer tolerance for ED automation in BEVs, which in turn may help increase market penetration and wider adoption of the technology.

This study attempts to fill the previously mentioned gap by implementing a selection of common methods in physical electric vehicle plants and evaluating them in terms of energy efficiency and feasibility using VHIL test data. GA, PSO, and DP were tested using physical vehicle dynamometer test data with a control-enabled electric Kia Soul utilizing a 2-wheel-drive chassis dynamometer. VHIL test performance of these methods is evaluated relative to each other as well as a baseline scenario. In the following sections, the design process for the ED system is described, along with the test setup, which includes information about the test vehicle and dynamometer calibration. The findings of the tests are displayed and explained in the results section, which is followed by a summary and conclusion.

Methodology

Eco-Driving System Design

Taking a systems-level view on the implementation of ED for autonomous BEVs, as seen in Figure 3, is proposed to facilitate more precise communication between universities, automakers, suppliers, governments, and other organizations.

A suite of sensors, a vehicle perception subsystem, a vehicle planning subsystem, and a vehicle plant subsystem, which includes a vehicle running controller, comprise the systems-level viewpoint. This systems model seeks to remain closely associated with the widely recognized systems-level perspective on autonomous BEV operation that employs energy management tactics.

Perception This system gets input from a collection of sensors that detect ambient information and can also be used to locate the vehicle's surroundings. An Autonomous Vehicle (AV) acquires environmental knowledge in two phases. The initial step is to examine the road ahead to determine if anything has changed, such as traffic signals and signs, a pedestrian crossing, or a barrier. The perception of nearby traffic is the focus of the second phase. Camera, LiDAR, Radar, Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I), Inertial Measurement Unit (IMU), Global Positioning System (GPS), and Inertial Navigation System (INS), as well as map and traffic data, are the most common sensors and data that comprise the sense and perception subsystems of autonomous vehicles (Figure 4) [23].

To evaluate EDC (Define) in the real world, the algorithms that generate the optimal ED trace must use only CAV-available information. The CAV's Advanced Driver Assistance System (ADAS) and V2I communication provide information. A CAV can generate ED path constraints with this data. Path constraints include allowable locations (distances along the vehicle path) and speeds at specific locations. Limitations on when and how fast the vehicle can travel at different points along its planned route make up what are called "path constraints" in this analysis.

Path Constraints. In autonomous vehicular control, the ego vehicle should not be designed to break traffic regulations,

FIGURE 3 System-level viewpoint of ED implementation for autonomous vehicles [22].

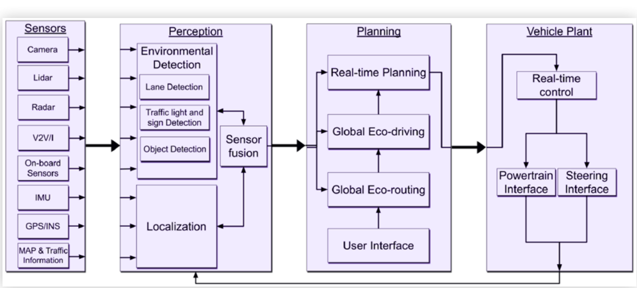
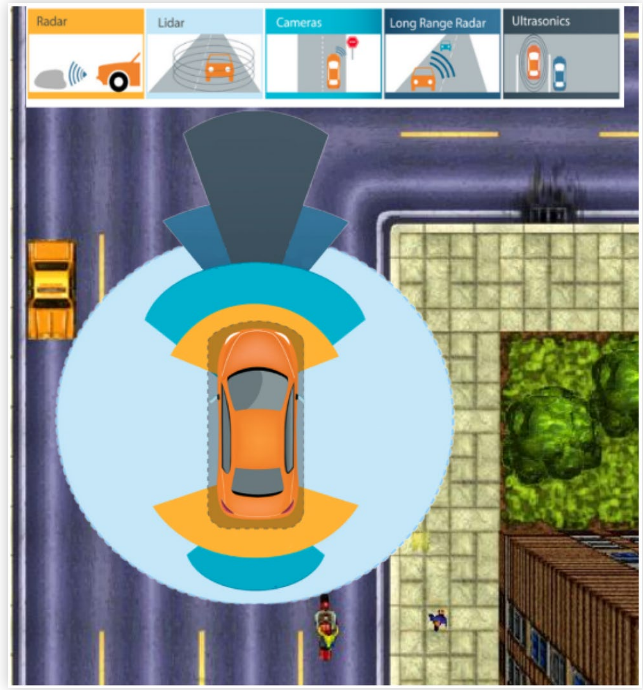


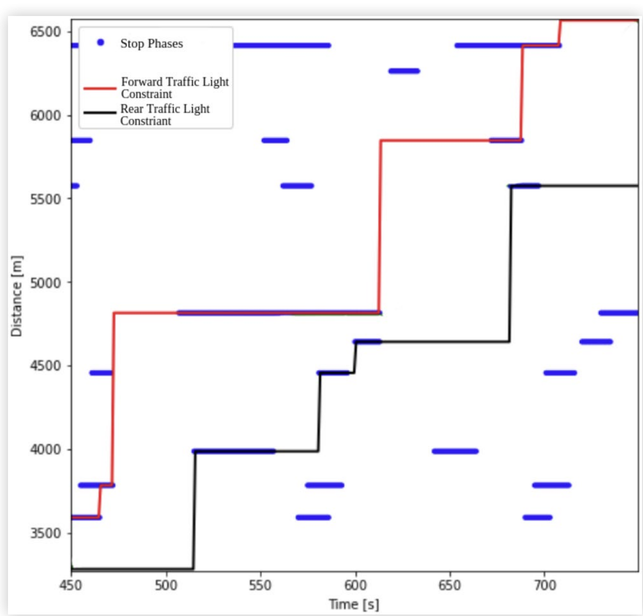
FIGURE 4 An illustration of the type and placement of sensors in an autonomous vehicle that enable the vehicle to perceive its surroundings [24].



even if doing so increases efficiency and/or trip time [25]. This indicates that the car should not exceed the speed limit, disregard traffic signals, or crash. Signal Phase and Timing (SPaT) can produce an inequality at the upper border if the ego vehicle is first in a queue.

Figure 5 depicts one such passageway. By restricting travel within the boundary corridor, the ego vehicle is more likely

FIGURE 5 An illustration of the type and placement of sensors in an autonomous vehicle that enables the vehicle to perceive its surroundings [27].



to behave in a way that is consistent with existing traffic patterns. The Intelligent Driver Model (IDM) discussed in [28] is used to choose stop phases to define the limits. For a specified duration of time, the IDM simulation is run, with the upper bound determined by the phases of the traffic lights through which the model vehicle passes, and the lower bound set by the phases of the same signals afterward. Given that the IDM model stands in for a typical motorist, the resulting corridor will accurately reflect typical traffic conditions. Using real-world SPaT [26] data to generate path boundaries adds a more realistic dimension to this research.

Phase and timing information for 19 traffic lights over a 4 mile path in downtown Fort Collins, CO was gathered in 2019. The authors gathered these statistics, and their methods are detailed in [28]. Working with the Fort Collins Traffic Operations facility, SPaT data covering many hours at each signal was gathered. A phase map was made using this information and the locations of the traffic lights along the route. The ego vehicle's speed must meet the inequality if it is to comply with traffic standards.

Planning (Eco-Driving) An optimal ED trace is computed by the planning subsystem, which takes into account the limits set by the perception subsystem. As described in the ED system design section, the planning system is assumed to contain an eco-routing, ED, and real-time planning controller, which is the lower level controller that implements eco-routing and ED in real-time. This study is only concerned with the high-level controller and is specifically focused on the ED controller.

Rules-Based Eco-Driving (RBED): This ED control method minimizes a vehicle's energy use using predetermined rules and historical and present data [29, 30, 31]. RBED strategies are easy to apply and are capable of enhancing fuel economy [32]. RBED has also been expanded from controlling a single vehicle to controlling eco-fleets using either cooperative or centralized methods [33,34].

Uniformly Discretized Trajectory Optimization (UDTO): A specified horizon (position or time) is discretized into a unique collection of points, and an optimization algorithm generates an ideal control action for each point. Dynamic Programming (DP) is a popular UDTO approach. Bellman [20] devised DP to create optimal control solutions for discretization. DP is a computationally intensive ED control approach, and it needs a huge amount of run-time. Much research has been done to solve this issue of DP as an ED control [35, 36, 37, 38]. Many works have suggested solver approaches with DP in a Model Predictive Control (MPC) formulation, which permits real-time DP-based solvers [39, 40, 41, 42, 43]. These studies used several methodologies to evaluate control costs. [36] came up with a Model Based Reinforcement Learning (MBRL) method for enhancing motor power control in electric vehicles, taking into account road slope but not traffic. Results-wise, MBRL was not noticeably different from DP for this situation. When it comes to ED control, DP and DP-derived methods are more common than reinforcement learning. Like DP, reinforcement learning has difficulty running in real time.

Spline Trajectory Optimization (STO): STO approach was the most often used in the literature for generating ED trajectories [16,44,45]. By adjusting the position, velocity, and acceleration of a spline's knots, ideal ED trajectories are produced. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are two optimization techniques that are frequently used in combination with STO. GA simulates natural selection to find an ideal solution. GA simulates natural selection by storing discretized issue choice factors as phenotypes, assessing their fitness, and mating the best phenotypes until a solution converges. Alan Turing introduced the approach in 1950, and Alex Fraser and Jack Crosby codified it in the 1970s [46, 47, 48]. GA can be implemented onboard for real-time control using pure serial processing, while parallel computing can significantly reduce run-time for GA-based STO [49, 50, 51]. PSO is the second often utilized heuristic method in ED literature. Russell C. Eberhart and James Kennedy developed the PSO model in 1995 in order to examine group member experiences [52]. It generates a field of candidate solutions (particles) and moves them in n-dimensional space according to their optimal solutions and the optimal global solution. Solutions are not necessarily optimal due to the search nature of PSO. The initial position of particles can influence optimality. The addition of mutation to PSO increases optimal solution convergence [53]. PSO was implemented in ED to optimize vehicle energy usage [50,53, 54, 55] and platoon behavior at junctions [56]. In a comparison between PSO and DP STO [55], PSO underperformed in energy efficiency but had a shorter run-time. PSO and GA were utilized to construct the best BEV trajectory [50]. Utilizing a PSO-GA hybrid algorithm yielded better results than using only one. Likewise, [54] investigated the use of PSO and GA to minimize the energy consumption of electric trains.

The methods selected for implementation were DP enabled UDTO, GA enabled STO, and PSO enabled STO with IDM serving as the baseline control to compare against. These methods are extensively defined in the author's previous paper [27]. Also In the team's previous study for optimal control solver methods, three different cost functions were evaluated. Acceleration l^2 Norm (Al2N) cost function, Road Power Cost (RPC) cost function, and Battery Power Cost (BPC) cost function. In this study, we just used the Battery Power Cost (BPC) cost function, which is an extension of the RPC cost function that takes the motor/inverter's efficiency into consideration, depending on the power needs. For further details, please see the authors' previous paper [27]. Figure 6 depicts an example trace generated by ED controllers in the planning subsystem.

Vehicle Plant For this study, a 2015 Kia Soul EV was selected as the vehicle of interest (Figure 7). This particular BEV was selected because the chassis dynamometer data for it is available from Argonne National Lab (ANL)'s Downloadable Dynamometer Database (D^3) [57] and because the research team owns a drive-by-wire capable physical vehicle. Table 1 shows general specifications for the 2015 Kia Soul EV used for this study.

Development of Eco-Driving Test Mode From predefined boundary cases in the author's previous study, four random representative drive cycle cases were selected to

FIGURE 6 An illustration of the type and placement of sensors as well as the ED trace generated in the Planning subsection [27].

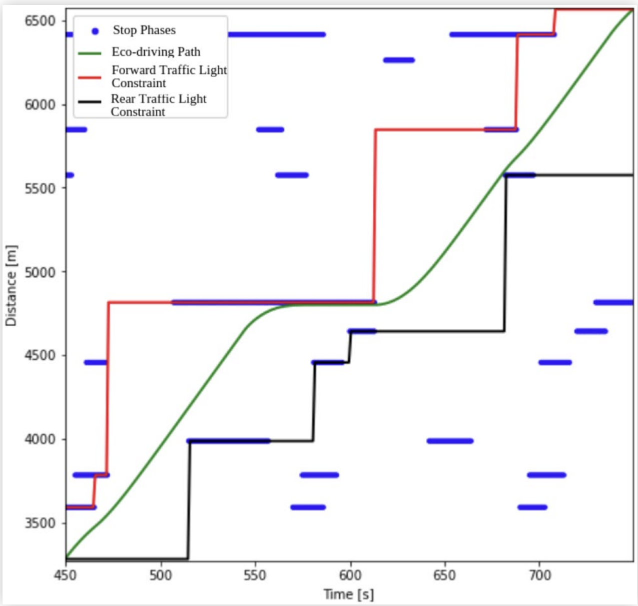
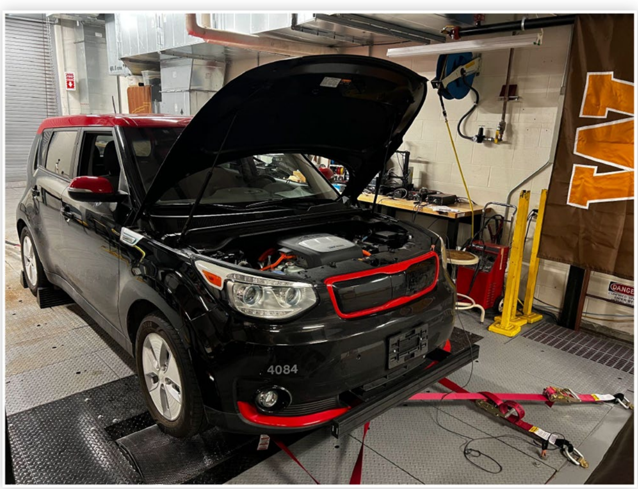


FIGURE 7 2015 Kia Soul on chassis dynamometer when being tested for this study.



evaluate on the chassis dynamometer. Speed vs. time and SOC vs. time comparisons between simulation traces for all methods on drive cycle number 0 (DC_0) are shown in Figure 8.

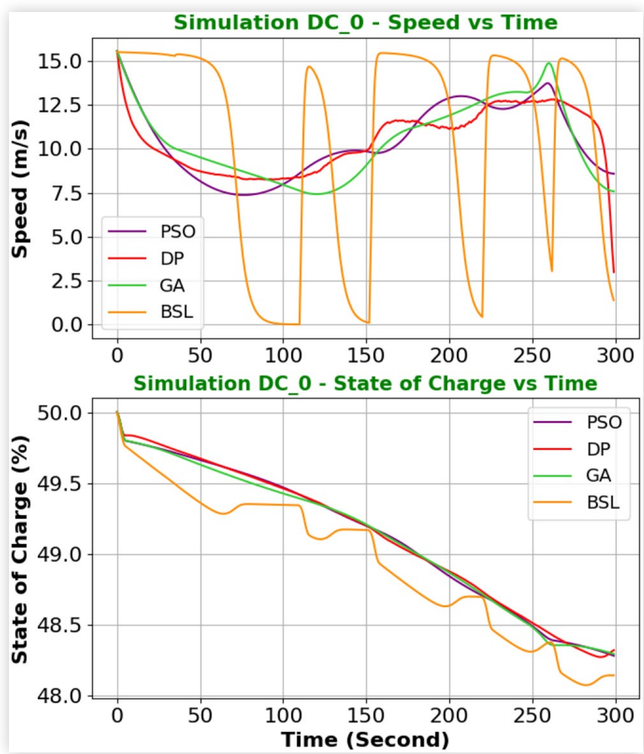
Experimental Design and Data Collection

The experiments were designed to measure the SOC of the vehicle (Kia Soul 2015 EV) running selected trajectory optimized ED traces as well as IDM as a baseline drive cycle on the chassis dynamometer. In our previous study, the authors evaluated the performance of the methods in generating optimal ED traces for 5-minute driving trajectories. To set up the experiments on the chassis dynamometer, first a driver had to specifically run the selected drive-cycles.

TABLE 1 Kia Soul 2015 EV specifications [58,59].

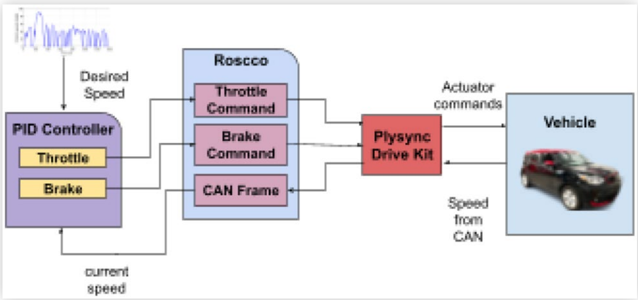
Parameter		Value	Units
Weights	Curb mass	1491.8	kg
	Delivered Curb mass	1664	kg
Dimensions	Wheelbase	2.6	m
	Length/Width	4.14/1.8	m
	Frontal Area	2.87	m
Electric Motor	Maximum Power	81	kW
	Maximum Torque	285	Nm
Battery	Useable Pack Energy	27	kWh
	Nominal Pack Voltage	360	V
EPA	Range	93	mile
	Fuel Economy	120 (City) 92 (Highway) 105 (Combined)	MPGe

FIGURE 8 Example speed vs. time and SOC vs. time comparison between simulation traces for all methods on drive cycle number 0.



Driver setup The driver's goal is to match the current speed of the vehicle on the chassis dynamometer to the targeted drive cycle speed during the test. This was done by developing

FIGURE 9 PID controller to vehicle integration pipeline using ROS and drive-kit.



a PID speed controller that tries to minimize the error between the vehicle's speed and a target speed (from the drive cycle). This is achieved by sending throttle and brake commands to the vehicle using the Robotic Operating System (ROS) [60,61]. Our team's research vehicle, the 2015 Kia Soul EV, is equipped with Polysync's drive-by-wire solution that allows the user to control the vehicle by sending brake, steering, and throttle commands through ROS. This system interacts with the vehicle through the corresponding actuators by sending controller area network (CAN) signals to the onboard computer. With the drive-by-wire system, we can also collect information from the CAN such as wheel speed, brake pressure, and steering wheel angle. Figure 9 depicts a pipeline for integrating PID controllers with ROS and the drive-kit in a vehicle.

Drive-Kit. Drive-kit is a drive-by-wire solution that can be installed in the Kia Niro HEV/PHEV/EV as well as the Kia Soul EV. When installed, the system provides an Application Programming Interface (API) that allows direct programming or use of middleware line ROS to command the vehicle directly, indirectly, or fully autonomously. The Drive-kit uses sensor imposition to control critical components such as braking, steering, and acceleration, while additional messages from the vehicle's OBD-II CAN provide additional information on the current vehicle states (e.g., steering angle and wheel speeds). Our research team owns The Polysync Drive-kit which is integrated in our research vehicle.

Speed Tracking Controller. A PID controller was developed to perform speed tracking and follow a given drive cycle. The drive cycle possesses time series data representing the speed of the vehicle (which we will call V_k) versus time (which we will call T_k). The speed tracking controller consists of finding the target speed (V_k) associated with its corresponding time (T_k) by matching the elapsed time T_j of our experiment with T_k. The error between the V_k and the vehicle's current speed (V_j) and fed to the PID controller. The PID controller tries to minimize the error between the target speed and the vehicle's current speed. The output of the PID controller is sent to the drive-by-wire system as a throttle command in order to match the drive cycle. Finally, since there is resistance from the chassis and other components, the PID controller was tuned to obtain better tracking performance. Figure 8 depicts the overall flow of our speed tracking controller for drive cycle matching.

FIGURE 10 Road load control module configuration from chassis dynamometer manufacturer (dynojet-224xLC).

Chassis Dynamometer Calibration The final step of test preparation was to calibrate chassis dynamometer parameters for accurate road load of the research vehicle during tests. Our research team owns a chassis dynamometer from DynoJet. Team's chassis dynamometer is capable of simulating road-load. By using the offered load control module integrated in the team's chassis dynamometer, we could calibrate the test setup. Figure 10 shows the environment of the dynojet software and load control module. The chassis dynamometer is calibrated based on the D^3 from ANL. Road load calibration is done for constant speed and the Urban Dynamometer Driving Schedule (UDDS) with respect to ANL data. The two tuned parameters, drag coefficient and vehicle mass, were tuned from assumed values in order to best match the battery SOC and battery power traces from the D^3 data. After tuning mentioned parameters, the 2015 Kia Soul EV on our research chassis dynamometer was able to match the D^3 data to within 0.4% with respect to the terms of SOC with Mean Absolute Percentage Error (MAPE) values of 0.82% and 1.552% respectively, for the constant speed test and UDDS. Figure 11 shows a comparison between ANL D^3 data and chassis dynamometer for UDDS on the 2015 Kia Soul EV.

Results

Each optimal ED controller method was evaluated in terms of its ability to produce energy efficient solution traces. The purpose of this study was, specifically, to compare the relative fuel economy improvements of several optimal ED controller methods using the chassis dynamometer. Figure 12 shows speed vs. time and SOC vs. time comparisons between physical vehicle dynamometer test traces for all methods on drive cycle number 0.

A representative example (drive cycle DC_0) is shown in Figure 13 which illustrates Speed vs. time and SOC vs. time comparison between physical vehicle dynamometer test and simulation traces for all methods on drive cycle number 0. As it can be seen, the physical vehicle dynamometer test traces are smoother compared to the simulation results because SOC

FIGURE 11 Comparison between ANL D[3] data and the calibrated chassis dynamometer for UDDS.

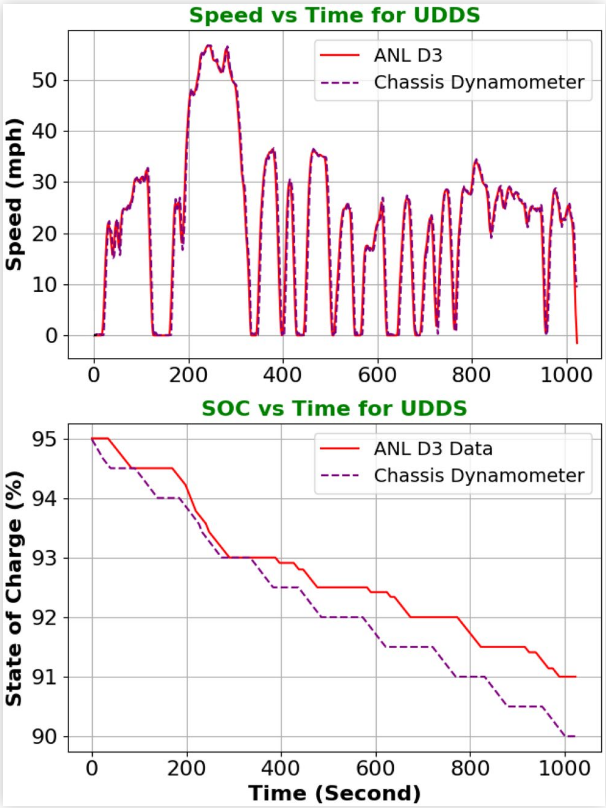


FIGURE 12 Example Speed vs. time and SOC vs. time comparisons between Dynamometer traces for all methods on drive cycle number 0.

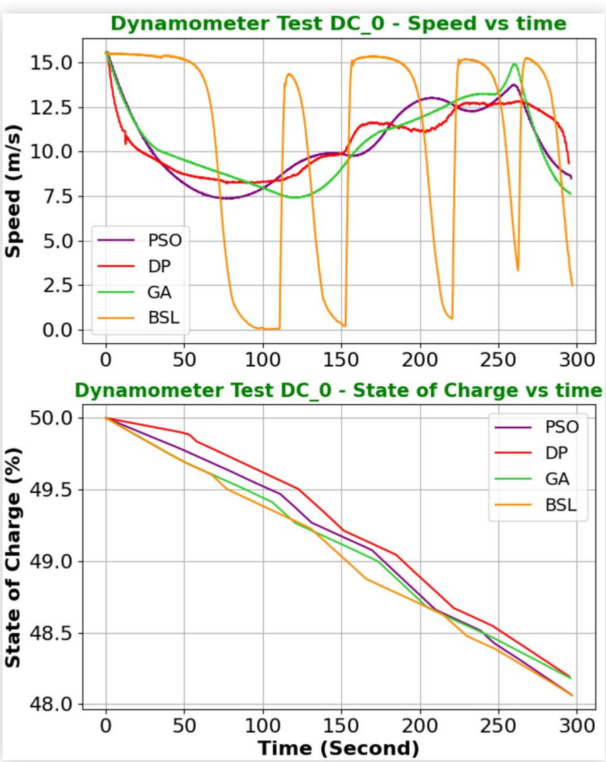
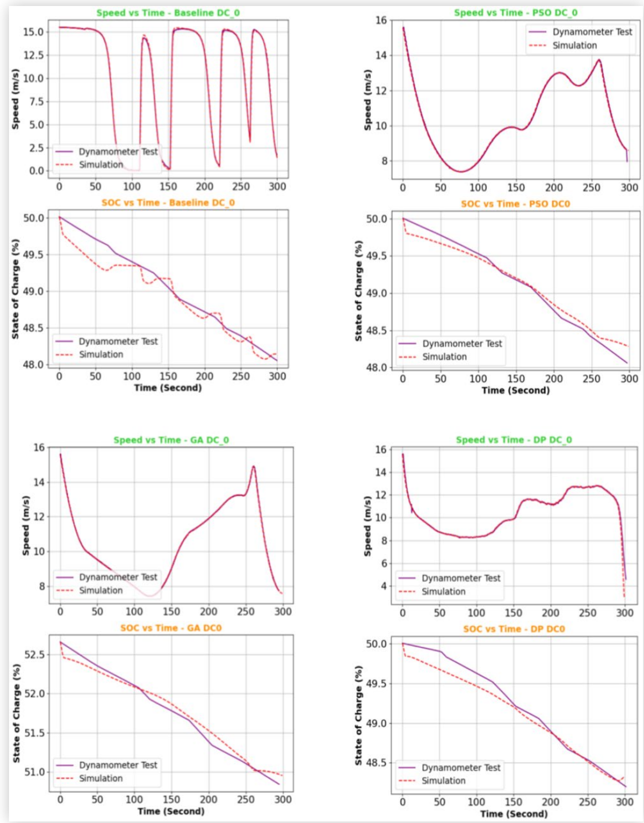


FIGURE 13 Example Speed vs. time and SOC vs. time comparison between physical vehicle dynamometer test and simulation traces for all methods on drive cycle number 0 (DC_0).



can be measured only with a precision of 0.5% which is the output SOC accuracy from CAN. Figure 13 shows speed vs. time and SOC vs. time comparisons between physical vehicle dynamometer test traces for all methods on drive cycle number 0. The results of the experiment in terms of fuel economy (FE) improvement over baseline are shown in Figure 14. physical vehicle dynamometer test results shown in Figures 14 verify the previous claim with FE improvement of 5.15%. physical vehicle dynamometer test FE improvements were 33.5% lower than the simulation. Also PSO test results show the same

FIGURE 14 FE improvement in terms of percentage over baseline for the studied methods.

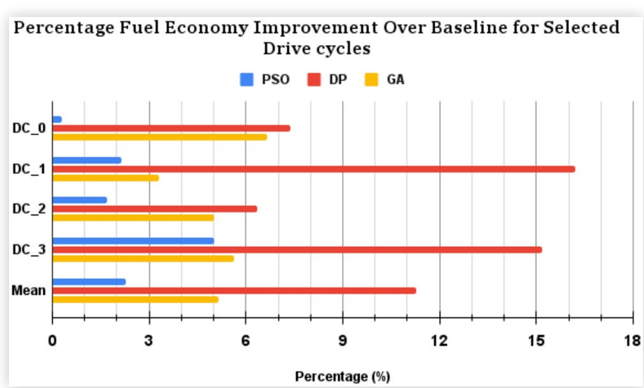


TABLE 2 Significance of comparative results (P-values) Purple means the column outperformed the row, blue means the row outperformed the column, and green means the difference was insignificant with 95% confidence.

Method	DP	PSO	GA
DP	1.0000	0.0018	0.0139
PSO	0.0018	1.0000	0.0123
GA	0.0139	0.0123	1.0000

pattern for FE improvement comparison between physical vehicle dynamometer test test results and simulation. PSO was able to improve FE less than other methods, 2.2%. This improvement was 62% lower than the simulation results. These errors could be rooted from many factors: sensor errors, instrumentation errors and losses, and slower response time of the vehicle vs the vehicle model in simulations. Overall, this can be concluded that DP has the best potential to improve FE. GA also, due to the relatively great FE improvements both in simulation and physical vehicle dynamometer tests and its lower computational cost, can be a great candidate for implementation.

The significance of the observed differences in effectiveness could not be assumed due to the considerable uncertainty regarding the FE improvement values. As a result, T-tests were conducted between all possible combinations of techniques, and the results are displayed in Table 2.

Conclusion

Synergistic benefits of connectivity, automation, and electrification contribute to a more efficient transportation system and a greener environment. In this study, first a systems-level view of autonomous ED was proposed, and subsystems including perception, planning, and vehicle plant were introduced. A great deal of research has been conducted on ED applications. Rules-Based Eco-Driving (RBED), Uniformly Discrete Trajectory Optimization (UDTO), and Spline Trajectory Optimization (STO) are the three primary classifications available in the literature. In our previous study, DP enabled UDTO, GA enabled STO, and PSO enabled STO were selected to be compared in terms of energy efficiency improvement capability in simulation. Not many studies evaluated these methods using physical vehicle dynamometer tests. This study attempts to fill the mentioned gap by testing these methods in a physical electric vehicle plant and evaluating these methods in terms of energy efficiency and practicality. Experiments were developed to assess the SOC of the vehicle (kia Soul 2015 EV) using optimized ED traces and IDM as a baseline driving cycle on the chassis dynamometer. A PID controller was utilized to build a link between the research vehicle's planned speed using Python, ROS, and drive-kit. The speed tracking ROS node sends and receives throttle, brake, and CAN frame messages. The PID controller was fine-tuned for tracking precision. The chassis dynamometer is calibrated using Argone's D^3 database (ANL). Constant speed and UDDS are calibrated for ANL data. The drag coefficient and vehicle mass were modified from anticipated values to match ANL D^3 battery SOC and power traces. Load road module provided by chassis dynamometer manufacturer (dynojet), was used to calibrate based on instantaneous loads. After calibration, the 2015 Kia Soul EV on our research chassis dynamometer matched the D^3 data to within 0.4% in terms of SOC with MAPE values of 0.82 and 1.552 for constant speed test and UDDS. Selected controller methods using real-world data were tested with a control-enabled electric Kia Soul EV utilizing a 2-wheel-drive chassis dynamometer. The physical vehicle dynamometer test performance of these methods is evaluated relative to each other as well as a baseline scenario. physical vehicle dynamometer test FE improvements were compared and evaluated with simulation results. In both simulation and physical vehicle dynamometer tests, DP improves FE by 11% followed by GA with 5.15% improvement in physical vehicle dynamometer test tests.

It can be concluded that DP has the greatest potential for real-world implementation because of its higher FE improvements compared to other studied methods. The fact that FastSim operates efficiently, in addition to being easily implementable in vehicles, suggests that original equipment manufacturers (OEMs) in the automotive industry and companies that develop autonomous vehicles may opt to implement DP in their own vehicles. This study is innovative since it demonstrates that drive-by-wire vehicle-hardware-in-loop may be used as an innovative method, making it easier to test and certify eco-driving systems for applications involving autonomous vehicles. Based on a chassis dynamometer, an integrated drive-by-wire physical vehicle, and simulation results, this system might be utilized early in the design phase to test and evaluate the integration of eco-driving control algorithms for autonomous and intelligent vehicles. This technology enables the testing and evaluation of complex eco-driving operations in a range of simulated environmental conditions and scenarios. This removes the need for test drives, which include their own dangers, expenses, and complications. Also, It is worth noting that incorporating such verified powertrain simulators (e.g. FastSim) into autonomous driving simulators such as CARLA could help researchers and autonomous vehicle developers to compare powertrains' energy efficiency and performance and estimate the impact of technology improvements for autonomous ED. In the future, it can be suggested to evaluate the real run-time and computation power comparison when these methods are configured and tested within the implemented planning subsystem. In the near future, this development will enable the implementation of optimal ED control for CAVs. With the widespread use of fully autonomous CAVs and vehicles, route planning will become entirely predictable, significantly boosting DP's efficiency. Therefore, the authors strongly advise that efforts to develop and execute in this direction should begin immediately.

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Definitions/Abbreviations

ADAS - Advanced Driver Assistance System

Al2N - Acceleration I2 Norm

ANL - Argonne National Lab

API - Application programming interface

AV - Autonomous Vehicle

BEV - Battery Electric Vehicle

BPC - Battery Power Cost

CAV - Connected and Automated Vehicles
D³ - Downloadable Dynamometer Database
DOE - Department of Energy
DP - Dynamic Programming
ED - Eco-driving
EM - Electric Motor
EPA - Environmental Protection Agency
EV - Electric Vehicle
GA - Genetic Algorithm
GPS - Global Positioning System
HEV - Hybrid Electric Vehicle
IDM - Intelligent driver model
IMU - Inertial Measurement Unit
INS - Inertial Navigation System
MBRL - Model Based Reinforcement Learning
MPC - Model Predictive Control
OBD-II - On-Board Diagnostic II
PHEV - Plug-in Hybrid Electric Vehicles
PM - Particulate Matter
PSO - Particle Swarm Optimization
RBED - Rules-Based Eco-Driving
ROS - Robotic Operating System
RPC - Road Power Cost
SPaT - Signal Phase and Timing
STO - Spline Trajectory Optimization
UDTO - Uniformly Discretized Trajectory Optimization
UDDS - Urban Dynamometer Driving Schedule
V2I - Vehicle to Infrastructure
V2V - Vehicle to Vehicle
V2X - Vehicle-to-Everything

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