Identification and Review of the Research Gaps Preventing a Realization of Optimal Energy Management Strategies in Vehicles

Zachary D. Asher,1 Amol A. Patil,1 Van T. Wifvat,2 Andrew A. Frank,3 Scott Samuelsen,2 and Thomas H. Bradley4

1Western Michigan University, USA
2University of California Irvine, USA
3University of California Davis, USA
4Colorado State University, USA

Abstract

The development of new vehicle control strategies that achieve improved fuel economy (FE) is an active subject of research due to the economic, environmental, and societal impact of transportation. These control strategies can be classified as either driving behavior modifications (e.g., Eco-Driving, Eco-Routing) or powertrain operation modifications (e.g., an Optimal Energy Management Strategy, or Optimal EMS). This literature review is focused on the Optimal EMS and seeks to develop a novel understanding of the current research gaps and to provide a novel comprehensive overview of initial studies addressing the identified research gaps. Research gaps are derived by utilizing a systems-level viewpoint of an Optimal EMS realization in vehicles and studying the subsystem integration readiness levels (IRLs). Identified research gaps include (1) incorporation of both perception and planning subsystems, (2) studying the effects of mispredictions on the planning subsystem, and (3) physical demonstrations of the planning subsystem. Studies which have begun to fill each research gap are identified, and recommendations are presented for future research to bridge each research gap. It is the authors’ contention that once the identified research gaps are closed by future studies, Optimal EMS will be achievable in modern vehicles resulting in improved transportation sustainability.
Introduction

Automobiles first achieved global adoption in the early twentieth century and continue to provide large economic and societal benefits. However, global adoption of automobiles also has drawbacks which include public safety risks from collisions, large contributions to energy consumption, contributions to air pollution, and contributions to climate change. To combat these drawbacks, technological advancements have been continually applied to the light-duty transportation sector. These technologies include safety-focused technologies such as the frontal collision warning, lane departure warning, and limited driver-assistance (collectively known as Advanced Driving-Assistance Systems, i.e. ADAS) as well as environment-focused technologies such as electrification and operation for improved efficiency [1].

These advancements evidence an ongoing vehicular evolution, in which human driving responsibilities are increasingly deferred to robust computerized systems of sensor technologies. With each stage of this evolution come improvements in vehicular safety as well as opportunities for minimizing fuel consumption.

The Importance of Minimizing Nonrenewable Fuel Consumption

In terms of global energy consumption, the transportation sector is the second largest consumer behind only the industrial sector. Transportation accounts for 30% of the world’s energy consumption, and the transportation energy demand is projected to increase 30% from current levels by 2040 [2]. Associated utilization of energy conversion devices, such as the internal combustion engine, results in issues spanning climate stability, domestic energy security, and human health risks from local air quality impacts.

The global transportation sector accounted for 64.5% of worldwide petroleum consumption in 2014 [2]. On a per-country basis, petroleum consumption is often unbalanced from domestic production, where disparity between the two creates the issue of energy security and vulnerability to geopolitical stability [3]. For example, a 2016 estimation shows that the United States alone paid $150 billion to the Organization of the Petroleum Exporting Countries [4, 5] and that estimated annual costs to ensure continued petroleum importation are around $200 billion [6].

Greenhouse gas emissions result in increased climate change, and the transportation sector was also responsible for 23% of global greenhouse gas emissions in 2014 [7, 8]. To combat these climate impacts, the Paris climate agreement has been adopted by most countries to limit greenhouse gas emissions and thus global warming to 2°C [9]. Limiting greenhouse gas emissions from transportation is proposed to be accomplished primarily through the increasing of FE with technologies such as improved vehicle operation efficiency and electrification [10]. It is widely accepted that without successfully stabilizing global climate, major degradation of the global ecosystem and environment will be imminent [8].

The transportation sector is also a major contributor to air pollution. Of the six primary air pollutants, transportation significantly contributes to worldwide nitrogen oxide/nitrogen dioxide (NOx), carbon monoxide (CO), volatile organic compounds (Voc), particulate matter (PM), and sulfur dioxide (SO2) [11]. As a result, 6.5 million premature deaths were attributed to air pollution in 2012, making it the world’s fourth-largest threat to human health [12]. Additionally, it has been shown that premature deaths from air pollution is expected to rise to 7.4 million by 2040 with the caveat that it is strongly region dependent [11].

Overall, increasing vehicle FE (reducing petroleum consumption) results in lower global energy consumption, lower greenhouse gas emissions, and lower air pollution emissions. Automotive FE standards, such as those adopted by the United States, Japan, Canada, Australia, China, Taiwan, South Korea, and others, have proven to be one of the most effective tools in controlling petroleum demand and greenhouse gas emissions in many regions and countries around the world [13].

The Evolution of Modern Vehicles

A major trend in the automotive field is that modern vehicles are gradually incorporating electrification to evolve from conventional vehicles (CVs) to hybrid electric vehicles (HEVs), plug-in HEVs (PHEVs), and fully electric vehicles (EVs) with increasing electrification projected to continue to beyond 2040 [14]. But, of those four vehicle types, HEVs and PHEVs are unique in that they have two sources of vehicle propulsion energy available. These vehicles can be powered from either battery power, engine power, or a combination of both. This additional operational degree of freedom unlocks potential for improved overall powertrain efficiency with intelligent control strategies. Examples of how this increased vehicle powertrain operational freedom can be used to reduce fuel consumption include regenerating energy during braking, storing excess energy from the engine during coasting, and modifying the power-split powertrain component operation for maximum efficiency [15,16].

A second trend, which is in stark contrast to the first 100 years of automobile development, is that the past 10 years have brought forth the most safety and convenience upgrades due to rapid advancements in computational technology [1]. The modern vehicle is one distinguished by an ability to perceive its environment by the use of sensor technologies and computer systems. This vehicle intelligence can manifest as driver assistance, provided by ADAS [17], or it can manifest as a vehicle which is afforded responsibility to make driving decisions independent of a human driver through autonomous technologies [18]. Near-future technologies include vehicle-to-vehicle communication (V2V), vehicle-to-infrastructure communication (V2I), and vehicle-to-everything communication (V2X). These technologies enable, for the first time, vehicle and/or

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powertrain control that can be predictive and forward-looking rather than simply backward-looking or reactive.

This second trend has resulted in researchers defining an intelligent vehicle. An intelligent vehicle is defined as a system that can sense the driving environment and provide information or vehicle control to assist the driver in improved vehicle operation [19]. Intelligent vehicle aspects include the ability to (1) sense the vehicle’s own status and its environment [20], (2) communicate with the environment [20], and (3) plan and execute appropriate maneuvers [19]. Note that the “environment” is defined as the vehicle surroundings which can include other vehicles, traffic lights, pedestrians, and so on. This increased environmental knowledge enables improved vehicle control strategies that can operate in tandem with inputs from a human driver.

The thesis of many researchers in this field is that the combination of these two trends (intelligent vehicle control and electrification) is a synergistic means to realize large fuel consumption improvements [21]. This article reviews numerous studies which show that the FE improvements with current intelligent HEVs are largely untapped. Existing intelligent electrified vehicles currently for sale include the 2020 Toyota Prius, 2020 Ford Fusion, 2020 Chevrolet Malibu, and others which offer HEV and PHEV architecture, pre-collision and pedestrian detection systems, lane departure alert with steering assist, adaptive cruise control with stop-and-go, blind-spot information with cross-traffic alert, and vehicle tracking through the global positioning system (GPS) [22, 23, 24, 25, 26].

Using Modern Vehicles to Minimize Fuel Consumption

There are three types of vehicle control that reduce fuel consumption for a drive cycle with a fixed starting point and a fixed ending point: (1) Eco-Driving, (2) Eco-Routing, and (3) an improved EMS. Eco-Driving and Eco-Routing decrease fuel consumption by decreasing the energy output of the vehicle through modification of the drive cycle. An improved EMS decreases fuel consumption by increasing the efficiency of the vehicle powertrain operation without modification of the drive cycle.

Eco-Driving reduces fuel consumption for all types of vehicles by implementing fuel-efficient driving behaviors along a fixed route which may alter the travel time. Due to this increase in travel time, it is challenging to convince drivers to adopt Eco-Driving habits [27]. If the driver input is removed or ignored, Eco-Driving can be formulated as an optimal control problem if the driving conditions along the route can be predicted. Current practical use of Eco-Driving is realized through a heuristic set of goals such as removing stops, traveling at a fuel-efficient speed (in general, this could be a higher or lower overall speed), and limiting acceleration and deceleration magnitudes, which together can achieve FE improvements of approximately 10% for modern vehicles and 30% for fully autonomous vehicles [28]. Research has typically focused on the FE impact of one intelligent vehicle technology, such as camera systems, radar systems, LiDAR, V2V, V2I, or V2X. As an example of a typical Eco-Driving study, one group of researchers used predictions of traffic light signal phase and timing (a V2I technology) to change driving behavior and demonstrated a FE improvement of 12-14% [29]. In practice, Eco-Driving is challenging to implement because most drivers do not like to give up control.

Eco-Routing reduces fuel consumption for all types of vehicles by exploring alternate vehicle routes between a fixed starting and ending location. Routes that minimize travel time enable social efficiency while routes that minimize fuel consumption enable vehicle energy output efficiency. Modern commercially available routing techniques are currently designed for minimum travel time (increase social efficiency) only. Eco-Routing is an active research subject that seeks to balance travel time and fuel consumption to maintain social efficiency and improve energy output efficiency. Research on a large geographic scale indicates that a 3.9% FE improvement for a 4.5% travel time increase is possible in Cleveland, Ohio and a 6.6% FE improvement for a 1.0% travel time increase is possible in Columbus, Ohio [30]. As vehicles become more intelligent, Eco-Routing can assist vehicles in real time, but several research gaps preventing real-world implementation of Eco-Routing have been identified [31].

An improved EMS seeks to reduce the energy consumption over a fixed drive cycle through improved powertrain operation efficiency. Typically, an optimal control problem is formulated and an Optimal EMS is derived. An Optimal EMS realizes FE improvements by explicitly or implicitly modeling vehicle operation and controlling the vehicle powertrain components to minimize fuel consumption. An Optimal EMS does not require a change in driver behavior; thus this FE improvement technique has a consumer acceptance advantage over Eco-Driving and Eco-Routing. An Optimal EMS can realize FE improvements for CVs and EVs, but the greatest FE improvements are realized in vehicles with more powertrain operation degrees of freedom such as HEVs and PHEVs. The exact FE improvement from an Optimal EMS is strongly dependent on the chosen drive cycle and vehicle architecture. As an example, one of the earliest Optimal EMS studies demonstrated a 28% FE improvement in a hybrid electric truck through optimal control of the gear shifting and battery charging and discharging [32]. FE improvements realized through Optimal EMS are the focus of this literature review.

To summarize, if FE is improved by modifying the drive cycle or route, then it is considered Eco-Driving and Eco-Routing, respectively, and it is not within the scope of this research. FE improvements over a fixed drive cycle are realized through an improved EMS or Optimal EMS, which is an active area of research in which 300+ papers have been published in just the last decade [33].

Optimal EMS Background

Developing and implementing an Optimal EMS has most commonly been posed as an application of optimal control. A mathematical optimization problem is formulated by defining a dynamic equation which describes the current state of the vehicle, a cost function that penalizes using fuel, and constraints that ensure a desired
final value of the battery state of charge is met, powertrain component limitations are not violated, and that the drive cycle is fixed. This optimization problem is also described in Equations 1-3.

**Dynamic Equation:**

New Battery State of Charge

\[ \text{New Battery State of Charge} = f \left( \text{Battery State of Charge}, \text{Engine Power}, \text{velocity} \right) \]

Eq. (1)

**Cost Function:**

\[ \text{Cost} = \text{Sum} \left( \text{mass of fuel used} \right) \]

Eq. (2)

**Constraints:**

- Desired battery state of charge at end of drive cycle
- Powertrain component physical limitations
- Fixed drive cycle

This framework can be utilized as either a second-by-second instantaneous optimization or as a global optimization which includes future vehicle operation prediction. The solution from either of these schemes is the minimum fuel consumption strategy (or Optimal EMS) which can be then be applied to operate the vehicle powertrain.

**Instantaneous Optimal EMS** An instantaneous Optimal EMS involves finding the optimal control strategy that minimizes fuel consumption at the instant in time for which sampled data is available. In practical implementation, the instantaneous Optimal EMS depends on the vehicle type.

Many aspects of modern CV engine and transmission control techniques are classifiable as an instantaneous Optimal EMS including deceleration fuel cutoff [34], fuel enrichment [35], variable valve timing [36], cylinder deactivation [37], and more. A basic example of the use of an instantaneous Optimal EMS in a CV is choosing the gear in which the vehicle will operate. When the vehicle is operating at fixed speed and fixed driver torque request, the vehicle requires a fixed power demand and the vehicle must choose one transmission gear in which to operate. A control strategy that selects the gear to minimize fuel consumption is an example of an instantaneous Optimal EMS.

For HEVs, large FE improvements can be achieved by restricting engine power operation to the minimum fuel consumption solution (also known as the ideal operating line) [38], which is the primary fuel-saving technique employed by HEVs today [39].

In PHEVs such as the Toyota Prius Prime and the Chevrolet Volt, studies using an instantaneous Optimal EMS have led to the “charge-depleting, charge-sustaining” EMS, where all excess battery power is used first, and then the battery charge is sustained afterwards [40]. This EMS is the standard operating mode for PHEVs to minimize nonrenewable liquid fuel consumption through maximization of renewable electrical energy consumption when prediction of future driving conditions is not available [41].

EVs also make use of instantaneous Optimal EMS improvements to minimize energy consumption and improve range through powertrain configuration optimization. Tesla Motors, an electric vehicle company, has multiple patents related to the use of an instantaneous Optimal EMS [42,43]. These patents improve the EV powertrain efficiency based on instantaneous driving conditions.

Instantaneous Optimal EMS remains an active research topic. Current efforts are focused on an implementation and quantification of the effects of an instantaneous equivalence calculation between electrical energy and fuel energy [44,45,46].

**Predictive Optimal EMS** A predictive Optimal EMS involves finding the optimal control strategy that minimizes fuel consumption for the window of time in which prediction data is available. Hundreds of papers have been written on the development and application of a predictive Optimal EMS in the past decade alone, but consistent real-world operation remains elusive [47,48]. Predictive Optimal EMS development can fit into one of three categories: (1) a globally Optimal EMS with deterministic prediction, (2) an Optimal EMS with stochastic prediction, and (3) a computationally limited Optimal EMS to enable practical implementation [49].

A globally Optimal EMS with deterministic prediction is derived using either dynamic programming (DP) [32] or Pontryagin’s minimization principle (PMP) which is based on calculus of variations [37]. When deriving a globally Optimal EMS using deterministic prediction, DP has been the overwhelming favorite of researchers due to its ease of use and robustness, and that no derivatives or analytic expressions are required [47,50]. A globally Optimal EMS with deterministic prediction is difficult to implement in practice because of the high computational cost, but it is still beneficial in simulation to define the upper practical limit on FE benefits for a given vehicle and drive cycle.

An Optimal EMS with stochastic prediction is used in applications where researchers are willing to forgo a guarantee of global optimal FE in favor of a robustness to stochastic prediction errors. In other words, stochastic derivation strategies are appropriate for applications where a small increase in FE over a wide range of drive cycles is desired. Stochastic derivation strategies include stochastic dynamic programming (SDP) [51] and adaptive equivalent consumption minimization strategy (a-ECMS) [52].

Lastly, a computationally limited practical implementation Optimal EMS also forgoes the guarantee of global optimal FE in favor of computationally efficient algorithms that can be used in current and near-future vehicles. Practical implementation derivation strategies in current vehicles include optimized rules-based control [53], ECMS [54], and model predictive control (MPC) using fast optimizers [55].

The significant research activity surrounding predictive Optimal EMS shows no signs of slowing down as evidenced by numerous Optimal EMS studies that continue to be published monthly. But unless a shift in research scope is applied to predictive Optimal EMS development, there will
Novel Contributions of This Research Gap Literature Review

Research that identifies and reviews existing research gaps is an essential part of scientific development [56], and it is common in multiple disciplines [57, 58, 59]. This article, which focuses on Optimal EMS in vehicles, builds from the concepts and literature discussed so far to deliver four novel contributions to the field:

1. A holistic and systems-level understanding of the subsystems and integrations needed to implement a predictive Optimal EMS in vehicles allowing for comparison between all studies in the field.
2. Application of technology, integration, and system readiness analysis to predictive Optimal EMS realization in vehicles.
3. A definition of the research gaps existing between the current state of the art and realization of predictive Optimal EMS usage in vehicles.
4. A review of initial studies that have begun targeting the identified research gaps.

Research Gap Derivation

Many studies of predictive Optimal EMS (now referred to as just “Optimal EMS”) conclude that vehicle perception, operation prediction, optimal control calculation, and optimal control actuation must all be achieved for successful implementation. However, a systems level understanding of how each of these pieces fit together is not as well defined.

To improve communication between academic researchers, the automotive industry, government stakeholders, and other entities, a systems-level viewpoint of Optimal EMS implementation, shown in Figure 1, is proposed. This systems-level viewpoint is intended to maintain close alignment with the well-accepted systems-level viewpoint of autonomous vehicle operation [18,60]. The systems-level viewpoint is composed of three subsystems: a vehicle perception subsystem, a vehicle planning subsystem, and a vehicle plant subsystem, which include a vehicle running controller.

The input to the Optimal EMS system is a suite of sensors which detect environmental information, thus defining vehicular surroundings (commonly referred to as the worldview in autonomous vehicle literature). This worldview can be used to generate a prediction of future vehicle states through artificial intelligence, stochastic modeling, regression analysis, and more. The vehicle state prediction can then be utilized in a mathematical optimization problem to determine powertrain operation that maximized FE. The maximum FE powertrain operation is then issued as a request to the vehicle running controller, which enforces component constraints and may be subject to various disturbances such as future vehicle state prediction error. The powertrain operation from the running controller is actuated in the vehicle plant, and the FE or energy consumption can be measured.

In order to assess the research gaps for an Optimal EMS implementation, a technology maturity framework is adopted. The Technology Readiness Level (TRL), originally proposed by the U.S. National Aeronautics and Space Administration, is one of the most prominent methods to assess technological maturity and help improve research and development outcomes [61]. The TRL scale has since been formally adopted worldwide despite known difficulties in application to large systems [62]. In response to these challenges, a popular and more comprehensive analysis is available which requires defining not only individual subsystem TRLs but IRLs, and an overall System Readiness Level (SRL)[63]. For the purpose of identifying the technological maturity of an Optimal EMS implementation, we adopt the SRL framework which requires that the TRL of each subsystem be defined and that the IRL of each subsystem integration be defined.

### TRLs

Table 1 describes the authors’ assessment of the TRL for each of the subsystems defined in Figure 1. The technologies from the first column of Table 1 are (1) vehicle perception for worldview building and prediction, (2) vehicle planning for determining fuel consumption reductions through optimal powertrain operation, and (3) usage of a physical vehicle plant to measure actual fuel consumption reductions. The perception subsystem receives sensor and signal inputs, defines vehicle surroundings, and thus computes future vehicle operation as an output. The planning subsystem receives the vehicle operation prediction as an input and computes the optimal control as an output. Note that the planning subsystem is only required to compute the optimal control and issue a control request, this subsystem is not tasked with achieving the...
optimal control in the vehicle; achieving the optimal control is accomplished with the vehicle running controller. The final subsystem is comprised of the vehicle running controller and the vehicle plant which receives the optimal control request and the current vehicle state as inputs; determines physically feasible vehicle operation that does not violate torque, battery state of charge, speed, acceleration, etc.; and limits and actuates the vehicle plant, thus producing a measurable FE or energy consumption as an output.

IRLs

Table 2 describes the authors’ assessment of the IRL for the three integration points possible in Figure 1. Descriptions of each integration scope are shown in column 1 of Table 2. While the TRL is used to evaluate individual subsystems, the IRL is used to evaluate the readiness for each subsystem to integrate with one another [54]. An accurate evaluation of each subsystem integration requires a larger scope than that of the individual subsystem, which typically consists of a simple input/output framework. Three conceptually unique integration points exist if the vehicle running controller and the vehicle plant are treated as one subsystem of high IRL: (1) perception and planning integration, (2) planning and control disturbances integration, and (3) planning and running controller/vehicle plant integration. Each of these integration points was found to have a low technological maturity, due to the starkly limited amount of research that uses these integration scopes.

SRL

Where the TRL analysis has been applied to individual subsystems, and the IRL has been applied to the integration between subsystems, the SRL analysis is the appropriate means of evaluation for the entire system of Optimal EMS implementation. Despite the relatively high TRLs of each subsystem, the low IRLs result in a low overall SRL as shown in Table 3. SRL analysis indicates that if the IRLs are improved, then the overall SRL will be improved and Optimal EMS can experience commercial production in vehicles.

Research Gap Analysis

Summary

SRL analysis has clearly identified three research gaps preventing Optimal EMS realization, all of which come from

<table>
<thead>
<tr>
<th>Integration and IRL</th>
<th>Integration description</th>
<th>IRL definition</th>
<th>IRL justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perception and planning integration: IRL 1</td>
<td>Receives sensor/signal data and computes the maximum FE control</td>
<td>“An interface between technologies has been identified with enough detail to allow characterization of the relationship”</td>
<td>Data transfer types are not standardized and worldviews are not standardized</td>
</tr>
<tr>
<td>Planning and control disturbances: IRL 2</td>
<td>Receives incorrect vehicle operation prediction but still requests FE-improved control</td>
<td>“There is some level of specificity to characterize the interaction between technologies through their interface”</td>
<td>There is limited research demonstrating improved FE with incorrect predictions</td>
</tr>
<tr>
<td>Planning and use of a vehicle plant: IRL 3</td>
<td>Receives vehicle operation prediction and achieves maximum FE control in the vehicle</td>
<td>“There is compatibility between technologies to orderly and efficiently integrate and interact”</td>
<td>There are a few demonstrations of this integration in the literature</td>
</tr>
</tbody>
</table>
subsystem integration. The integrations that need to be addressed by research include:

1. Performance of integrated perception and planning models
2. Performance of a planning model subject to disturbances
3. Performance of a planning subsystem integrated with a physical vehicle plant

This article will now thoroughly review high-quality studies that include one of these integrations only. As previously discussed, there are hundreds of papers incorporating Optimal EMS, but most of them do not include one of these integrations.

The following sections are dedicated to each integration research need. A definition of the research scope is defined, a relevant research question is proposed, and literature matching the scope and research question is reviewed. Studies that do not include sufficient integration to meet the relevant research scope are not included.

### Research Gap 1: Performance of Optimal EMS with Actual Velocity Predictions

Projects addressing research gap 1 would include all of the following: (1) a perception model with sensor/signal inputs and future vehicle operation prediction as an output, (2) a planning model that uses future vehicle operation prediction to derive an Optimal EMS, and (3) FE results. Only literature that meets each of these three requirements will be reviewed in this section. Note that some researchers have included this scope across multiple publications (see Michigan Technological University [64,65] and North Carolina State University [66,67] studies), but since there isn’t one complete study that includes these three components, they were omitted from full discussion here. This first research gap was identified by applying an integration scope that includes the perception and planning subsystems as shown in Figure 2.

The FE results from an Optimal EMS that uses actual predictions from a perception model are not well understood. Are there certain types of perception algorithms that work better than others (e.g., Markov chain, autoregression, machine learning, etc.)? Are there certain sensor inputs that enable high-quality predictions (e.g., GPS, ADAS detections, V2V, weather information, etc.)? Although numerous vehicle sensor and signal information could be used, an Optimal EMS may only require a limited worldview with a low computational cost perception algorithm to achieve optimal FE control. An as-yet unanswered research question could be posed as:

- What worldviews can enable an Optimal EMS?

Starting in 2008, the earliest and presently most cited research pertaining to perception, Optimal EMS planning, and FE results comes from researchers at the University of Florida and the University of Wisconsin-Milwaukee. Their study used V2I and GPS signals as inputs into a perception model. The perception model was then able to output vehicle operation predictions using an analytical traffic model [68], and the approach was later revised to employ an artificial neural network (NN) [69]. The use of a NN to characterize a driving pattern was found to be effective, and FE improvements using an Optimal EMS in a PHEV were realized.

In 2013, researchers at the University of Stuttgart, Germany, have integrated a perception model and a planning model. Their perception model is based on repeated drive cycles of a hydraulic hybrid garbage truck. They use GPS and a current vehicle state to characterize and store a drive cycle. The perception model creates predictions by using the stored drive cycle data for current vehicle operation. The planning Optimal EMS only determines the optimal time to implement the hydraulic power. This team demonstrated significant FE improvements using an Optimal EMS in a PHEV were realized.
improvements when driving behavior was predicted but noted that inclusion of traffic information is required for real-world implementation [70].

In 2014, researchers at the University of Minnesota applied a traffic model to predict future vehicle velocity with V2V and V2I as inputs. They employed PMP to derive their Optimal EMS and realized a modest FE improvement. FE gains were limited by the difficulty of incorporating constraints [71].

Then, in 2015, researchers from the University of California at Berkeley recognized the important relationship between perception and planning and investigated three perception models for use with a MPC Optimal EMS. They used previous driving data and the current vehicle state as inputs to test an exponentially varying perception model, a stochastic Markov chain perception model, and an NN perception model [72]. Their results show that the NN perception model with an Optimal EMS computed using DP on a validated model of a 2010 Toyota Prius. The maximum FE improvement was achieved using 30 seconds of prediction [74]. The next study used V2V communication as an additional sensor/signal input to study the trade-offs between V2V and non-V2V signal inputs with an Optimal EMS. The results of this second study show that predictions without V2V are more accurate at shorter prediction horizons while predictions with V2V are more accurate at longer prediction horizons [75]. Another follow-on study used custom camera detections relevant for velocity prediction [76], travel time data, as well as current and previous vehicle velocity and GPS data as the sensor/signal inputs, again with a shallow NN and an Optimal EMS. These currently available sensor inputs enabled an overall FE improvement, and it was also shown that travel time data negatively impacts predictions for city-focused driving, but positively impacts highway-focused driving [77].

Starting in 2017, researchers from the Beijing Institute of Technology, China, demonstrated greater and more consistent FE improvements with the aid of historical velocity data and a NN perception model to inform an ECMS-derived Optimal EMS [78]. Note that ECMS only requires the computation of an equivalence factor to determine engine/battery operation, but for real-world driving, the optimal equivalence factor must be continually updated; thus there is an improvement from prediction as discussed by other researchers [79]. Additionally, other researchers from the Beijing Institute of Technology used previous drive cycle data as an input into a Markov chain and NN perception subsystem with an Optimal EMS based on a genetic algorithm. These researchers were able to realize significant FE improvements in the highway fuel economy test (HWFET), LA92, and Japanese urban driving cycles even when running in real time [80].

Two additional studies that include a similar scope were published in 2017 from researchers at Jilin University, China, and in 2018 from researchers at Tongji University, China. The study from Jilin University incorporated self-reported driving behavior and predicted traffic information to develop what

### TABLE 4: Summary of existing research that includes the integration scope of perception, Optimal EMS planning, and FE results, thus addressing research gap 1.

<table>
<thead>
<tr>
<th>Research group</th>
<th>Sensors/signals</th>
<th>Perception model</th>
<th>Planning techniques</th>
<th>Vehicle model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Univ. of Wisconsin Milwaukee 2009 [68,69]</td>
<td>GPS, V2I</td>
<td>Traffic model, NN</td>
<td>DP</td>
<td>Generic hybrid SUV</td>
</tr>
<tr>
<td>Univ. of Stuttgart 2013 [70]</td>
<td>Vehicle state, route, GPS</td>
<td>Database look-up</td>
<td>Custom hydraulic power optimization</td>
<td>Parallel hydraulic hybrid truck</td>
</tr>
<tr>
<td>Univ. of Minnesota 2014 [71]</td>
<td>V2V, V2I</td>
<td>Traffic model</td>
<td>PMP</td>
<td>Generic power-split HEV</td>
</tr>
<tr>
<td>Univ. of California Berkeley 2015 [72]</td>
<td>Vehicle state, drive data, V2I</td>
<td>Exp. varying Markov chain &amp; NN</td>
<td>MPC</td>
<td>Generic power-split HEV</td>
</tr>
<tr>
<td>Colorado State University 2017, 2018 [74, 75, 76, 77]</td>
<td>Vehicle state, drive data, V2V, GPS, V2V, travel time, ADAS</td>
<td>NN</td>
<td>DP</td>
<td>Validated 2010 Toyota Prius</td>
</tr>
<tr>
<td>Beijing Institute of Technology 2017, 2018 [78,80]</td>
<td>Vehicle state, drive data</td>
<td>Markov chain and NN</td>
<td>a-ECMS and genetic algorithm</td>
<td>Generic power-split HEV</td>
</tr>
<tr>
<td>Jilin University 2017 [81]</td>
<td>Travel info., driving behavior, GPS</td>
<td>NN</td>
<td>Improved a-ECMS</td>
<td>PHEV</td>
</tr>
<tr>
<td>Tongji University 2018 [82]</td>
<td>Vehicle state, drive data</td>
<td>Markov chain</td>
<td>DP</td>
<td>Hybrid electric bus</td>
</tr>
<tr>
<td>Univ. of California Riverside 2019 [83]</td>
<td>Traffic data</td>
<td>Deep NN</td>
<td>Reinforcement learning</td>
<td>Generic power-split PHEV</td>
</tr>
<tr>
<td>Univ. of Michigan 2019 [84,85]</td>
<td>Vehicle state, GPS, V2V, V2I</td>
<td>Deep NN, Markov chain, conditional Gaussian, and more</td>
<td>DP</td>
<td>Validated 2017 Toyota Prius Prime</td>
</tr>
</tbody>
</table>
they call “improved a-ECMS” which realized a larger FE improvement than a-ECMS [81]. The study from Tongji University compares ECMS, a-ECMS, and DP with a velocity prediction perception model [82]. These researchers conclude that DP with a real-world velocity prediction may provide the best FE improvement.

Recent trends have begun to implement advancements in machine learning and have replaced shallow NNs with deep NNs. This was first demonstrated by researchers at the University of California Riverside where a deep reinforcement network was implemented as a perception and planning subsystem in that traffic data was input and optimal control of a generic PHEV was the output. This technique resulted in a 16.3% FE improvement in simulation [83]. Additionally, research that was conducted at the University of Michigan and then transitioned to Western Michigan University explored a variety of perception models including autoregressive moving average, shallow NN, long short-term memory (LSTM) deep NN, Markov chain, and conditional linear Gaussian models. It was determined that the LSTM deep NN provided the best prediction fidelity (measured in mean absolute error) [84] which realized a FE improvement of 3% in a dynamometer validated model of a 2017 Toyota Prius Prime [85].

Each of these studies has been summarized in Table 4 using columns to show the important differences between the studies (i.e., which sensors/signals were used, what perception model was used, etc.). Taken together, these papers show that the best results were obtained when a NN is used as a perception model. But there is still no comprehensive study investigating the effect of different groups of signal inputs or perception models. Future research in this area will likely leverage the recent breakthroughs in deep learning for an improved perception model.

Research Gap 2: Performance of Optimal EMS when Subjected to Disturbances

Projects addressing research gap 2 would include all of the following: (1) a planning model that uses future vehicle operation prediction to derive an Optimal EMS, (2) disturbances in actual control from disturbances such as mispredictions, and (3) FE results. Literature that meets each of these three requirements will be reviewed in this section. This second research gap was identified by applying an integration scope that includes the planning subsystem and disturbances as shown in Figure 3. Note that other researchers have also identified this as an important research gap [42].

The FE results from an Optimal EMS subjected to disturbances are not well understood. Are there certain types of disturbances that have large FE impacts (e.g., speed-up mispredictions, unrecognized stop signs, current vehicle weight mispredictions, outside wind speed/direction changes, etc.)? Are there certain Optimal EMS types that are more resistant to certain types of disturbances (e.g., stochastic DP, MPC, ECMS, etc.)? Although numerous disturbances are possible, perhaps some disturbances are worse than others or perhaps most disturbances have no impact. An as-yet unanswered research question could be posed as

- How sensitive are optimal FE strategies to worldview/prediction scope, fidelity, and uncertainty?

In 2006, researchers at the National Renewable Energy Laboratory utilized DP for half battery size and full battery size PHEVs to compare optimal solutions for drive cycles of various lengths. They found that for drive cycle distances exceeding the PHEV all electric range (charge depleting strategy), the optimal solution seeks a “blended” strategy (a mix of charge depleting and charge sustaining strategies) such that the minimum battery state of charge is achieved at the end of the drive cycle [86]. But in considering the “cost of being wrong,” they demonstrated that if the vehicle distance is less than predicted for optimal control, there is a significant FE loss. In other words, if the Optimal EMS assumes the trip will be longer than it actually is, the vehicle will not use all the stored electrical energy and thus requiring more liquid fuel consumption.

In 2011, researchers at the Ohio State University conducted a study using alternate drive cycles as a prediction input error for two real-time implementable Optimal EMS: a modified MPC strategy and a-ECMS [87]. They found that the FE cost of predicting the wrong drive cycle was small for both of the Optimal EMS, but no baseline FE results were shown.

In 2012, researchers at Clemson University investigated the effects of stochastic misprediction errors on a-ECMS [88]. This group used the U.S. EPA drive cycles of Urban Dynamometer Driving Schedule (UDDS), US06, and HWFET for 25, 50, 75, 100, and 150 miles. Their results show a degradation in FE at all values of mean absolute percent error
greater than zero. But no correlation between error magnitudes and FE was found.

Then in 2014, researchers at the University of Michigan built upon their initial SDP-derived Optimal EMS from 2004 [51] and studied the impact of driving alternate drive cycles [89]. These researchers used a large real-world drive cycle data set to derive a new stochastic Optimal EMS. The stochastic Optimal EMS was demonstrated to improve FE over a baseline strategy when tested on alternate drive cycles. Additionally, a researcher from this project has continued to study the effect of uncertain events on energy management for HEV, PHEV, EV, and fuel cell vehicles. A generalized stochastic model was proposed that incorporates uncertain route predictions, destinations, charging locations, traffic predictions, historical speed, grade data, and driver models. SDP is used with a generic PHEV sedan on a drive cycle similar to the FTP72, and the results show increased battery usage when approaching the destination [90].

Starting in 2015, researchers at Colorado State University expanded on initial research [91-93] by rigorously investigating the effect of real-world velocity prediction errors and vehicle parameter prediction errors on FE realized through Optimal EMS. A set of driving-derived disturbances such as mispredicted stops, traffic, and route changes were compared using a validated model of a 2010 Toyota Prius using an Optimal EMS derived using DP. It was found that a wide range of FE improvements can still be achieved despite what would seem to be significant velocity mispredictions [50]. The work was also expanded into a new application that uses a precomputed and robust Optimal EMS applied to acceleration event predictions [93].

In 2016, researchers at the University of Minnesota investigated an Optimal EMS which was focused on fast computation through separable programming while also being subjected to disturbances [94]. Using a traffic simulator to develop drive cycles and 30 different vehicle platforms, they compared their Optimal EMS to DP and showed favorable results. When the drive cycle predictions were subjected to a normally distributed random prediction error, FE improvements were maintained at a 3% mean absolute deviation percentage, but FE improvements were lost at a 6% mean absolute deviation percentage.

Starting in 2017, a group of researchers from the Beijing Institute of Technology studied the influence of an imprecise driving cycle prediction on an Optimal EMS implemented in a PHEV. First, they derived an Optimal EMS using particle swarm optimization assuming a precise prediction of the future drive cycle is available. Next, they analyzed the influence of imprecise prediction and proposed an online correction algorithm based on a fuzzy logic control strategy. This overall system is demonstrated on the US06, EUDC, and REP05 drive cycles and they show that their method significantly improves the results [95]. An additional study from the Beijing Institute of Technology analyzed the effect of driving style on a-ECMS-derived FE improvements. They validated their model by conducting experiments with five different drivers (three moderate and two aggressive) in a real-world urban cycle. They also developed tools to precisely recognize the instantaneous driving style, and they compare their a-ECMS to traditional ECMS. The FE improvement was significant but depended on correct prediction of the driving style [96].

Each study addressing this research gap has been summarized in Table 5, using columns to show the important differences between the studies. Taken together, these papers show that most Optimal EMS derivations are robust to prediction errors. But there is still no comprehensive study investigating the effect of different types of prediction errors on different Optimal EMS derivations.

**Research Gap 3: Performance of Optimal EMS in Real Vehicles**

Projects addressing research gap 3 would include all of the following: (1) a planning model that uses future vehicle operation prediction to derive an Optimal EMS; (2) actual vehicle

<table>
<thead>
<tr>
<th>Research group</th>
<th>Drive cycle</th>
<th>Planning technique</th>
<th>Error type</th>
<th>Vehicle model</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Ohio State Univ. 2011 [87]</td>
<td>Real world</td>
<td>MPC, a-ECMS</td>
<td>Alternate drive cycle</td>
<td>Generic power-split PHEV</td>
</tr>
<tr>
<td>Clemson University 2012 [88]</td>
<td>UDDS, US06, HWFET</td>
<td>a-ECMS</td>
<td>Stochastic</td>
<td>Generic power-split PHEV</td>
</tr>
<tr>
<td>Univ. of Michigan 2014, 2016 [89-90]</td>
<td>Real world, FTP72</td>
<td>Stochastic DP</td>
<td>Alternate real-world, uncertain events</td>
<td>Prototype Volvo S-80, generic PHEV</td>
</tr>
<tr>
<td>Colorado State University 2015-2018 [91, 92, 93]</td>
<td>Real world</td>
<td>DP</td>
<td>Real world, vehicle power</td>
<td>Validated 2010 Toyota Prius</td>
</tr>
<tr>
<td>Univ. of Minnesota 2016 [94]</td>
<td>Traffic simulation</td>
<td>Separable programming</td>
<td>Stochastic</td>
<td>Generic power-split PHEV</td>
</tr>
<tr>
<td>Beijing Institute of Technology 2017, 2018 [95-96]</td>
<td>Real world, US06, EUDC, REP05</td>
<td>DP, a-ECMS</td>
<td>Slightly off target</td>
<td>Commuter PHEV</td>
</tr>
</tbody>
</table>
Literature that meets each of these three requirements will be reviewed in this section. This third research gap was identified by applying an integration scope that includes the perception and planning technologies as shown in Figure 4.

The FE results from an Optimal EMS that uses actual predictions from a perception model are not well understood. Are there certain types of perception algorithms that work better than others (e.g., Markov chain, autoregression, machine learning, etc.)? Are there certain sensor inputs that enable high-quality predictions (e.g., GPS, ADAS detections, V2V, weather information, etc.)? Although numerous vehicle sensor and signal information could be used, an Optimal EMS may only require a limited worldview with a low computational cost perception algorithm to achieve optimal FE control. An as-yet unanswered research question could be posed as:

- What operational challenges have not been validated and quantified in the conceptual work?

There is limited research that includes Optimal EMS planning, vehicle plant considerations, and FE results because offline computations, hardware-in-the-loop, and vehicle-in-the-loop research is expensive and the technologies for specific vehicles are proprietary. Because of this, initial research in this area has been focused on a rules-based Optimal EMS due to the ease of implementation [97, 98, 99, 100]. But there are research programs designed to overcome cost and proprietary information challenges such as FutureCar, EcoCAR, and the most recent NEXTCAR program, which is an initiative to reduce vehicle energy consumption by 20% [101]. These programs have enjoyed significant success and, in some cases, have been the catalyst for research addressing research gap 3 at universities.

In 2001, a computationally limited Optimal EMS implementation was achieved by researchers at the Ohio State University who implemented ECMS in an SUV as part of the FutureTruck program [102]. This initial demonstration produced promising FE results and inspired rigorous research of ECMS at the Ohio State University that has been ongoing for nearly two decades [103]. This research is also being explored as part of the NEXTCAR program [104].

Starting in 2008, researchers at the University of Michigan took their initial SDP-derived Optimal EMS [51] and first included engine-in-the-loop simulations to closer approximate a real vehicle [105] and then applied it in a prototype vehicle [106]. Although a hardware problem prevented them from attaining a full FE assessment from their SDP controller, they concluded that an Optimal EMS can be implemented in a real vehicle and requires minimal tuning.

Starting in 2011, researchers at IFP Energies Nouvelles, or French Institute of Petroleum, have successfully implemented an Optimal EMS in a hardware-in-the-loop simulation for a diesel hybrid vehicle. Diesel-powered vehicles add the extra challenge of incorporating emissions minimization into the optimization scheme. Using ECMS, they were able to significantly improve FE, while reducing oxides of Nitrogen (NOx, an emissions constituent) through parallel HEV architecture [107, 108, 109, 110].

In 2012, researchers at the Eindhoven University of Technology, the Netherlands, have successfully implemented an Optimal EMS using PMP to achieve a moderate FE improvement over a baseline, rules-based, control strategy on a hybrid electric truck. The FE improvement was demonstrated on a variety of drive cycles, including road grade variations. They achieved success in implementing the Optimal EMS on the vehicle’s engine control unit (ECU) with the assistance of stored solutions from offline computations [111].

Also, in 2012, researchers at Shanghai Jiao Tong University, China, demonstrated FE improvements over a baseline rules-based control strategy using a hardware-in-the-loop real-time simulation. These researchers derived an Optimal EMS using a form of DP and then used the solution to train a NN. The trained NN then accepted drive cycle inputs and output an improved control strategy [112].

In 2013, researchers at the University of Stuttgart, Germany, incorporated a perception model and a planning model into an actual vehicle. They were able to test their Optimal EMS using a rapid prototyping unit on their hybrid hydraulic truck. When testing on a closed track, this team found FE improvements as well as instances of reduced FE when compared to the baseline control strategy; though these results were briefly mentioned and no detailed analysis was shown [70].

Also, in 2013, researchers at the University of Salento, Italy, investigated the implementation of a PMP-derived Optimal EMS in a hardware-in-the-loop simulation of a custom-built series PHEV. These researchers investigated multiple local drive cycle section prediction cases. The researchers were able to demonstrate an overall FE improvement despite needing to reduce the complexity of their Optimal EMS planning formulation to satisfy real-time running constraints [113].

In 2016, researchers from Tsinghua University, China, proposed an Optimal EMS that is a combination of offline SDP and ECMS for a plug-in hybrid electric bus. The Optimal EMS was tested in simulation and hardware-in-loop using real-world urban bus routes. The real-world bus route data is
divided into segments according to the position of bus stops which are used as inputs into the SDP Optimal EMS formulation. The results are then converted into a three-dimensional lookup table of parameters for the real-time operation ECMS. They observed a significant increase in FE but noted that the hardware-in-the-loop case consumes slightly more fuel than the simulated one [114].

In 2017, researchers from Arizona State University and Clemson University proposed an integrated vehicle hardware-in-the-loop approach to address the limitation associated with a traditional hardware-in-the-loop approach. Both rules based and ECMS were tested using the integrated vehicle hardware-in-the-loop approach implemented on a parallel through-the-road HEV. The drive cycles analyzed include the FHDS, FUDS, and US06. The general results show strong correlation between the simulated vehicle and the integrated vehicle hardware-in-the-loop approach. The results from physical vehicle fuel consumption measurements indicate that the ECMS achieved a higher FE [115].

Also in 2017, researchers from the Beijing Institute of Technology proposed an EMS using Markov Chain Monte Carlo velocity prediction with average filtering and quadratic fitting, a stochastic MPC as the Optimal EMS, and hardware-in-the-loop experiments. When tested on the Chinese Typical Urban Driving Cycle (CTUDC), the observed a substantial FE improvement over a rules-based strategy, but less FE than a globally Optimal EMS [116].

In 2018, researchers from Kunming University of Science and Technology, China, investigated a PMP Optimal EMS that controls engine on/off state using simulations and hardware-in-the-loop experiments. The proposed strategy was demonstrated on a variety of drive cycles such as the UDDS, HWFET, and New European Driving Cycle (NEDC), and real-world cycles. They selected a charge-depleting/charge-sustaining strategy as their lower bound and a globally Optimal EMS through DP as the highest FE bound. The results show a significant FE improvement at a low computational cost that can be practically implemented [117].

As part of the NEXTCAR program, researchers at Michigan Technological University have explored an optimized blended mode strategy in the Chevy Volt PHEV. DP is implemented and FE improvements between 2 and 12% are measured in a fleet of four instrumented Chevy Volts [118].

Each of the initial studies addressing this research gap has been summarized in Table 6, using columns to show the important differences between the studies. Taken together, these studies show that through gradual incorporation of vehicle plant components through software-in-the-loop, hardware-in-the-loop, and vehicle-in-the-loop experiments, Optimal EMS implementation that improves FE can be realized. Numerous research opportunities still exist that could fill this research gap by focusing on the demonstration of an Optimal EMS in a variety of vehicle operational environments with a variety of vehicle types, platforms, and powertrains.

**TABLE 6** Summary of existing research that includes the integration scope of Optimal EMS planning, a vehicle plant, and FE results, thus addressing research gap 3.

<table>
<thead>
<tr>
<th>Research group</th>
<th>Drive cycle</th>
<th>Planning technique</th>
<th>Vehicle plant model</th>
<th>Vehicle realization</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Ohio State Univ. 2001, 2019 [102, 104]</td>
<td>Real world ECMS</td>
<td>2000 Chevrolet Suburban</td>
<td>Actual vehicle</td>
<td></td>
</tr>
<tr>
<td>Eindhoven University of Tech. 2012 [111]</td>
<td>Real world PMP</td>
<td>Parallel hybrid electric truck</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Shanghai Jiao Tong University 2012 [112]</td>
<td>CTBDC Iterative DP</td>
<td>Power-split hybrid electric bus</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Univ. of Stuttgart 2013 [70]</td>
<td>OC Bus Cycle, Real world Custom hydraulic power opt.</td>
<td>Parallel hydraulic hybrid truck</td>
<td>Actual vehicle</td>
<td></td>
</tr>
<tr>
<td>Univ. of Salento 2013 [113]</td>
<td>Real world PMP</td>
<td>Prototype series PHEV</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Tsinghua University 2016 [114]</td>
<td>Real world SDP, ECMS</td>
<td>Parallel PHEB</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Beijing Institute of Technology 2017 [116]</td>
<td>CTUDC Stochastic MPC</td>
<td>Plug-in hybrid electric bus</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Kunming Univ. of Science and Technology 2018 [117]</td>
<td>UDDS, HWFET, NEDC, real World PMP</td>
<td>Power-split PHEV</td>
<td>Hardware-in-the-loop</td>
<td></td>
</tr>
<tr>
<td>Michigan Technological University 2019 [118]</td>
<td>Real World Limited preview DP</td>
<td>Chevy Volt PHEV</td>
<td>Actual vehicle</td>
<td></td>
</tr>
</tbody>
</table>
Conclusions

In this literature review, vehicle control for optimal FE was introduced by discussing methods that increase FE by modifying vehicle velocity (Eco-Driving, Eco-Routing) as well as a method that increases FE without modifying vehicle velocity (Optimal EMS). Upon further exploration of Optimal EMS literature, it was discovered that despite the existence of several hundred studies addressing the concept of Optimal EMS, integration and system-level research gaps still exist. When systems-level analysis is applied, three research gaps are identified: Optimal EMS planning with perception, Optimal EMS planning including disturbances, and Optimal EMS execution with a vehicle plant. In other words, gaps in academic knowledge exist regarding

1. An understanding of essential sensors and signals for perception and prediction enabling optimal FE vehicle control
2. A deep understanding of disturbance types that can affect optimal FE vehicle control
3. The operational and real-world vehicle implementation challenges of optimal FE vehicle control.

A review of insightful research efforts in each of these areas was presented, and recommendations for future efforts that can advance the body of knowledge of Optimal EMS were discussed. Overall, four novel contributions were made. They include a systems-level viewpoint of the subsystems and integrations needed for Optimal EMS allowing comparisons between all studies in the field, system readiness analysis applied to predictive Optimal EMS realization in vehicles, formal definitions and example research questions for existing research gaps, and a targeted review of initial studies that address the research gaps.

Engineering research is responsible for providing actionable ideas for industry incorporation. Because there are hundreds of combinations of vehicle architectures, drive cycles, and optimization routines, there have been hundreds of research papers showing the same result: an Optimal EMS can increase FE [42]. We present this comprehensive literature review on the Optimal EMS concept with the objective of focusing the efforts of the research community on increasing the IRL of the various subsystems and integrations needed for Optimal EMS planning with perception, Optimal EMS planning including disturbances, and Optimal EMS execution with a vehicle plant. In other words, gaps in academic knowledge exist regarding

Contact Information

Zachary D. Asher
Western Michigan University
Zach.Asher@WMich.edu

Abbreviations

ADAS - Advanced Driver-Assistance System
CTUDC - Chinese Typical Urban Driving Cycle
CV - Conventional Vehicle
DP - Dynamic Programming
ECMS - Equivalent Consumption Minimization Strategy
ECU - Engine Control Unit
EMS - Energy Management Strategy
EPA - Environmental Protection Agency
EV - Electric Vehicle
FE - Fuel Economy
GPS - Global Positioning System
HEV - Hybrid Electric Vehicle
HWFET - Highway Fuel Economy Test
IRL - Integration Readiness Level
MPC - Model Predictive Control
NEDC - New European Driving Cycle
NOx - Oxides of Nitrogen
Optimal EMS - Optimal Energy Management Strategy
PHEV - Plug-in Hybrid Electric Vehicle
SDP - Stochastic Dynamic Programming
SRL - System Readiness Level
SUV - Sport Utility Vehicle
TRL - Technology Readiness Level
UDDS - Urban Dynamometer Driving Schedule
V2I - Vehicle-to-Infrastructure Communication
V2V - Vehicle-to-Vehicle Communication

References


