

UNIVERSITÉ DU QUÉBEC À TROIS-RIVIÈRES

INTEGRATED SPEED AND ENERGY MANAGEMENT OPTIMIZATION FOR  
FUEL CELL ELECTRIC VEHICLES: TOWARD REAL-TIME CONTROL IN  
DYNAMIC AND WINTER DRIVING CONDITIONS

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## **Abstract**

Fuel efficiency in fuel cell hybrid electric vehicles (FCHEVs) depends strongly on the coordination between energy management and vehicle motion. Conventional approaches address energy management strategies (EMS) and speed planning separately, which often leads to suboptimal energy use. This thesis addresses this limitation by proposing a co-optimization framework that integrates both layers and adapts to real-world driving conditions.

The proposed approach builds on a detailed analysis of energy recovery mechanisms in electric and fuel cell vehicles, identifying key limitations of existing control strategies. An improved sequential method is first introduced, where a dynamic deceleration constraint is incorporated into speed planning. This constraint respects regenerative braking limits and improves energy recovery without increasing the complexity of the EMS. The thesis then proposes a fully integrated co-optimization strategy that simultaneously optimizes the vehicle speed trajectory and power distribution. This integrated formulation enhances regenerative braking performance and improves fuel economy under diverse driving conditions. To enable real-time implementation, a model predictive control (MPC) framework is developed that accounts for traffic interactions and low-friction road conditions. The proposed controller is validated through Hardware-in-the-Loop (HIL) testing, demonstrating its feasibility for practical applications.

Overall, the results show that integrated motion and energy control significantly improve fuel economy and energy recovery in FCHEVs. The offline integration shows up to 36 percent advantage in hydrogen consumption compared to sequential benchmarks. Moreover, the online integrated method demonstrates suitability for online application with 25 ms median solving time.

## Résumé

L'efficacité énergétique des véhicules électriques hybrides à pile à combustible (FCHEV) dépend fortement de la coordination entre la gestion de l'énergie et le mouvement du véhicule. Les approches conventionnelles traitent la stratégie de gestion de l'énergie (EMS) et la planification de la vitesse de manière séparée, ce qui conduit souvent à une utilisation sous-optimale de l'énergie. Cette thèse répond à cette limitation en proposant un cadre de co-optimisation qui intègre ces deux niveaux et s'adapte aux conditions de conduite réelles.

L'approche proposée s'appuie sur une analyse détaillée des mécanismes de récupération d'énergie dans les véhicules électriques et à pile à combustible, permettant d'identifier les principales limites des stratégies de contrôle existantes. Une méthode séquentielle améliorée est d'abord introduite, dans laquelle une contrainte dynamique de décélération est intégrée à la planification de la vitesse. Cette contrainte respecte les limites du freinage régénératif et améliore la récupération d'énergie sans augmenter la complexité de l'EMS. La thèse propose ensuite une stratégie de co-optimisation entièrement intégrée, qui optimise simultanément la trajectoire de vitesse du véhicule et la répartition de puissance. Cette formulation intégrée améliore les performances du freinage régénératif et l'économie de carburant dans diverses conditions de conduite. Afin de permettre une application en temps réel, un cadre de commande prédictive (MPC) est développé en tenant compte des interactions avec le trafic et des conditions de faible adhérence. Le contrôleur proposé est validé par des essais Hardware-in-the-Loop (HIL), démontrant sa faisabilité pour des applications pratiques.

Dans l'ensemble, les résultats montrent que l'intégration du contrôle du mouvement et de la gestion de l'énergie améliore significativement l'économie de carburant et la

récupération d'énergie dans les FCHEV. L'intégration hors ligne montre un gain pouvant atteindre 36 % en consommation d'hydrogène par rapport aux approches séquentielles de référence. De plus, la méthode intégrée en ligne démontre sa pertinence pour une application en temps réel, avec un temps de résolution médian de 25 ms.

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## Liste des symboles

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|                  |                                 |
|------------------|---------------------------------|
| $m$              | Vehicle mass                    |
| $\mu_{rr}$       | Rolling resistance coefficient  |
| $C_D$            | Aerodynamic drag coefficient    |
| $A$              | Frontal area                    |
| $r_{wh}$         | Wheel radius                    |
| $fd$             | Final drive ratio               |
| $Q_{bat}$        | Battery capacity                |
| $\eta_{fd}$      | Final drive efficiency          |
| $F_{res}$        | Total resistance force          |
| $F_v$            | Driving force at the wheel      |
| $\theta$         | Road grade                      |
| $P_v$            | Wheel power                     |
| $P_{fd}$         | Power at final drive output     |
| $P_{brake}$      | Mechanical brake power          |
| $P_{elc}$        | Electric power                  |
| $P_{fc}$         | Fuel cell power                 |
| $P_{bat}$        | Battery power                   |
| $P_m$            | Mechanical power of the motor   |
| $\tau_{em}$      | Electric motor torque           |
| $\omega_{em}$    | Electric motor speed            |
| $\omega_{wheel}$ | Wheel rotational speed          |
| $SOC$            | State of charge of the battery  |
| $\dot{m}_H$      | Hydrogen mass flow rate         |
| $LHV_{H_2}$      | Lower heating value of hydrogen |

|              |                                     |
|--------------|-------------------------------------|
| $V_{oc}$     | Open-circuit voltage of the battery |
| $R_b$        | Internal resistance of the battery  |
| $I_b$        | Battery current                     |
| $\eta_{bat}$ | Battery efficiency                  |
| $T$          | Total travel time                   |
| $s$          | Traveled distance                   |
| $v$          | Vehicle speed                       |
| $a_x$        | Longitudinal acceleration           |
| $a_y$        | Lateral acceleration                |

## **Chapter 1 - Introduction**

### **1.1 Motivation**

The increasing scarcity and cost of fossil fuels limit the development of transport systems and energy accessibility for communities. On the other hand, ongoing environmental concerns and public demand for sustainable development have been the hallmarks of recent years [3]. These factors have shifted focus toward clean energy alternatives for transport, such as electric vehicles (EVs), hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs). FCEVs offer zero-emission transport and short refueling time (compared to EVs). Despite these advantages, FCEVs suffer from a lack of refueling infrastructure in many areas. This problem highlights the importance of increasing energy efficiency and reducing fuel consumption in FCEVs [4].

There have been comprehensive studies on conventional vehicles aimed at reducing energy consumption, ranging from improvements in aerodynamic design and tire rolling resistance to the development of more efficient internal combustion engines. These advancements have played a significant role in enhancing vehicle performance and reducing fuel use. In addition to the approaches applied to conventional vehicles, new energy vehicles are introducing entirely new powertrain architectures, such as those found in electric vehicles (EVs), hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs), which open up further opportunities for improving efficiency. These alternative drivetrains not only allow for better energy conversion and utilization but also enable advanced strategies such as regenerative braking and energy management optimization, which are not feasible in traditional powertrains. As a result, new energy vehicles present a broader design space and greater potential for innovation in reducing energy consumption [5, 6]. The emergence of autonomous driving is also bringing a whole set

of new tools to enhance energy consumption in a vehicle. The development of automated vehicles offers significant potential for enhancing vehicle energy efficiency and optimizing regenerative braking systems. Automated vehicles can utilize sensors, communication technologies such as V2I and V2V, and artificial intelligence to predict and respond to driving conditions more effectively than human drivers. This predictive capability enables automated vehicles to adopt eco-driving techniques, such as maintaining optimal speeds, minimizing unnecessary acceleration and deceleration, and anticipating traffic signal changes. In the past, eco-driving was a set of guidelines provided to human drivers to help them achieve a more efficient driving pattern. But now, with automated driving, a vehicle is capable of precisely following any speed profile, profiles that are calculated to be both efficient and safe [7, 8].

As an example, in conventional vehicles, pulse-and-glide speed profiles, which include rapid acceleration followed by a coasting phase, are more efficient. Electric vehicles, which have the advantage of regenerative braking, could benefit from a different speed profile, as they can recover braking energy [9]. Autonomous systems can optimize regenerative braking by precisely controlling braking events to maximize energy recovery. For instance, they can calculate the exact timing and force needed for braking to ensure the highest possible conversion of kinetic energy to electrical energy, thereby extending the driving range and improving fuel efficiency [10]. These techniques can significantly reduce energy consumption and enhance the overall efficiency of the vehicle. These eco-driving strategies aim to improve fuel efficiency, reduce energy consumption, and enhance driving comfort and safety. They can be formulated as an optimal control problem (OCP) to determine the optimal speed [8, 11–14].

Most of these studies on FCEVs focus exclusively on the EMS layer and tank-to-wheel

efficiency, without integrating speed profile optimization. While numerous studies have investigated the EMS and speed planning separately, the integration of the two methods requires further study.

Additionally, in areas such as Quebec, the effects of hilly roads in winter conditions are a crucial factor to consider when integrating EMS and speed planning for online applications. The combination of steep inclines, slippery surfaces, and varying road traction poses significant challenges for maintaining safe and efficient vehicle operation. In such environments, energy recovery through regenerative braking can be limited, and power demands may fluctuate rapidly depending on the road grade and driving conditions. Therefore, any practical implementation of EMS and speed planning must account for these dynamic factors to ensure effective energy management and real-time adaptability during winter driving scenarios.

In short, the emergence of automated driving, public demand for clean transport, and the advent of vehicles with hybrid powertrains are creating a critical convergence area in modern vehicle technology, as depicted in Figure 1.1. This area introduces great potential to improve energy efficiency and promote a more sustainable transport system.

## **1.2 Literature Study**

Increasing energy efficiency in conventional vehicles has been extensively investigated in the literature. Efforts include the use of energy-efficient technologies such as advanced engines that reduce engine losses, eliminating idling losses, studying lightweight materials, improving aerodynamics, and enhancing component efficiency throughout the powertrain pipeline [3, 15–20]. This is a vast research field, and when considering intelligent driving and hybrid vehicles, two subproblems emerge as important directions

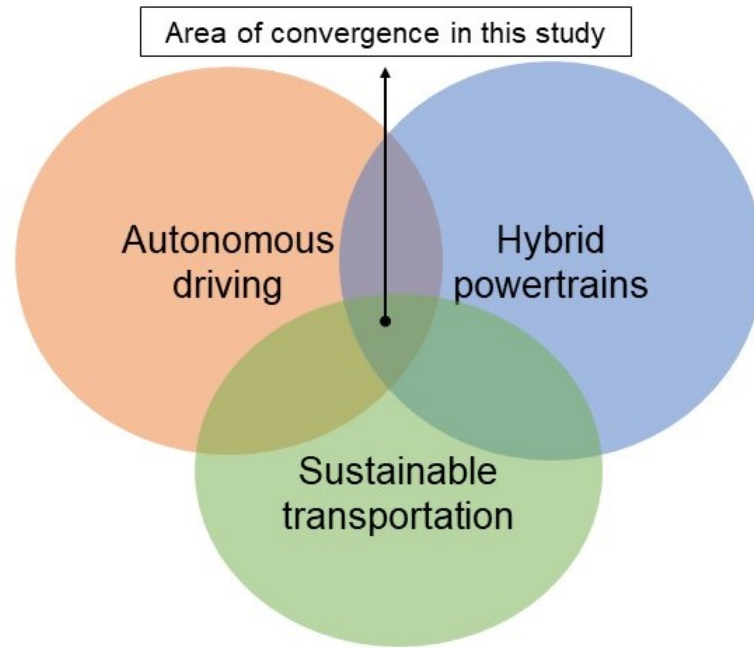


Figure 1.1 The convergence area that the presented study covers

of study. The first is speed planning, which involves determining the optimal speed to minimize fuel consumption based on external factors and the vehicle's motion model (wheel-to-distance optimization). The second is EMS optimization, which determines the optimal power distribution between the fuel cell and the battery, based on powertrain dynamics and system constraints (tank-to-wheel optimization) [21, 22]. Various methods have been employed for EMS, including rule-based approaches [23–25], optimization-based approaches [26–28], and learning-based approaches [29–31]. Methods implemented in EMS also have a considerable impact on the overall fuel efficiency of vehicles. Several studies have explored the use of speed prediction to improve the performance of EMS [32, 33]. For instance, Ma et al. [34] introduced a real-time EMS for FCHEVs that incorporates a variable-horizon velocity prediction scheme to enhance the effectiveness of a Pontryagin's Minimum Principle-based strategy. Similarly, Jia et al. [35] developed a predictive EMS for fuel cell hybrid buses, integrating both speed

and passenger flow forecasts through bi-directional Long Short-Term Memory (LSTM) networks. In another effort, Kofler et al. [36] proposed a predictive EMS for fuel cell vehicles that leverages route-based long-term power demand prediction to optimize the state-of-charge (SOC) trajectory over the trip.

One widely used approach is to address these two layers sequentially, first solving the speed planning problem, then using the resulting optimal speed as an input for the EMS layer. This approach, due to its lower complexity, handles nonlinearities more easily and runs faster. However, its decoupled structure often leads to suboptimal results. An alternative is the integrated, or co-optimization, approach, which solves speed planning and EMS simultaneously. This method considers all relevant state variables and control inputs related to vehicle dynamics (such as speed, distance, time, and force) and powertrain architecture (such as fuel consumption and battery state of charge), resulting in a more comprehensive and effective optimization process. The main drawback of this approach, however, is its high computational cost and long runtime [37, 38].

In [39], a bi-level optimization framework was introduced to address the coordination of speed planning and EMS for FCEVs navigating signalized intersections. Similarly, Liu et al. [40] proposed a convex bi-level approach for the same application; however, this method excluded regenerative braking constraints and involved simplifications to preserve convexity. Expanding the scope beyond intersections, a sequential optimization strategy was presented in [41], where speed planning, EMS, and energy recovery were treated in sequence for FCEVs operating in dynamic urban environments. This framework was further extended in [42] to account for curving scenarios. To improve the applicability in online contexts, [43] proposed a convex bi-level optimization considering electric motor and final drive losses along with fuel cell efficiency. While this approach was

suitable for real-time applications, its layered structure limited the potential for optimal improvements in both speed trajectories and energy consumption. A similar two-layered strategy was applied to a fleet-level context for fuel cell trucks in [44]. Beyond individual vehicle control, [45] introduced a centralized spacing control strategy for connected and automated FCEV platoons using gradient-based model predictive control (MPC). A hierarchical framework combining nonlinear MPC with a multi-objective EMS was proposed in [46] for FCHVs. In related work, Zhang et al. [47] designed a hierarchical eco-driving controller for connected HEVs that integrates predictive cruise control with a cost-to-go-based EMS. Similarly, in [48], a hierarchical strategy was used to combine eco-driving and EMS for HEVs under car-following conditions. In [49], a sequential optimization method was introduced for car-following scenarios involving multiple lead vehicles on slippery roads. However, the study made an unrealistic assumption by considering a flat road with no turning. In [50], deep reinforcement learning is employed for speed planning and eco-driving under varying road–tire adhesion coefficients. Despite the increasing use of sequential and hierarchical methods to manage complex traffic and energy scenarios, their decoupled structure often leads to suboptimal results. This limitation arises because energy source behavior is not directly accounted for in the speed planning process [51].

For further improvement, some studies integrate the speed planning layer and EMS into a comprehensive problem to find optimal speed and power allocation simultaneously as co-optimization. This approach results in a more complex problem that demands higher computational effort. A joint optimization of speed and energy management was introduced in [52] for series HEVs, with results compared to a hierarchical framework for the optimal control problem. The joint optimization outperformed the sequential method. In [53], a data-driven approach was proposed for eco-driving and energy management

strategy optimization of a plug-in HEV to reduce computational effort. However, this method heavily relies on high-quality data sets for training neural networks, and if these data sets do not represent diverse real-world scenarios, their performance could degrade. In [54], the authors present a cooperative optimization framework that integrates Adaptive Cruise Control and EMS using a Soft Actor-Critic algorithm for an FCEV in a car following scenario. In another work focused on car following driving, Chen et al. proposed an integrated eco-driving framework for FCHEVs that optimizes speed and energy management collaboratively, using a deep deterministic policy gradient-based algorithm [55]. In [37], a sequential optimization was compared to co-optimization for an FCEV using dynamic programming. While the superior performance of co-optimization in an FCEV was demonstrated, the complexity of the problem was reduced by limiting the control actions as the input controls were simplified into five modes (e.g., full regenerative braking, full braking, coasting, cruising, and full propulsion), which could be unrealistic. Additionally, model simplifications, such as ignoring electric motor losses, affected the results. An analytical method for the co-optimization of speed planning and energy management in automated Parallel HEVs at multi-signal intersections was developed in [56].

### **1.3 Problem Statement and Conceptual Framework of This Study**

Based on the reviewed literature and the drive toward higher energy efficiency, several important gaps remain. First, energy harvesting and recovery in FCEVs have not been studied in a comprehensive way. Energy recovery returns energy that would otherwise be lost back into the powertrain. Some studies have explored this potential, but an investigation devoted solely to FCEVs is necessary to fully understand the available opportunities. The same need exists for energy harvesting. Because FCEVs differ

fundamentally from conventional vehicles, these new possibilities must be examined in detail. It is also important to explore how energy recovery and harvesting can adopt new approaches as autonomous driving shapes the future of transportation systems.

Second, after exploring the emerging field mentioned above, it is important to investigate how the sequential optimization of speed planning and EMS can be improved. Although this approach yields sub-optimal results, it remains popular among researchers due to its simplicity and fast computation. A key question is how to minimize energy loss caused by the separate nature of speed and EMS optimization in the sequential framework.

Next, there is a need for a study on an integrated approach that handles speed planning and EMS simultaneously. The few existing studies on this topic often overlook the use of comprehensive vehicle models and real-world data. Due to its complexity, this approach is less commonly tested across diverse driving scenarios and road conditions.

Finally, there is significant room for improvement in the integrated approach, particularly regarding real-time implementation and fast computation. Since the main drawback of this approach remains its computational burden for online applications, there is a strong demand for studies that develop faster integrated methods. In addition, the impact of winter conditions on the integrated method, particularly factors like reduced tire grip and slippery road surfaces, clearly requires thorough investigation. These conditions can significantly affect vehicle dynamics and energy management, and thus must be carefully considered in both modeling and real-time implementation.

In addition to the mentioned gaps, the lack of realistic and validated components in vehicle models is a key challenge in EMS and speed optimization studies for FCEVs. For example, when comparing parameters such as the fuel cell maximum power and battery

capacity of a commercial FCEV like the Toyota Mirai with those in [37, 39–41, 57–59], a considerable gap becomes evident between the models and real-world applications.

#### 1.4 Contribution of This Project

The literature review and problem analysis reveal a clear gap in the current research, highlighting an opportunity for the presented study to contribute to more energy-efficient driving in intelligent FCEVs. By addressing this gap, the study aims to support the development of advanced strategies that enhance both energy management and driving performance under real-world conditions.

The principal contributions of this work lie in two key directions. First, it aims to bridge the gap between intelligent energy-efficient driving strategies and powertrain optimization by integrating these two aspects into a unified framework. This integration allows for coordinated decision-making that improves overall vehicle efficiency. Second, the study proposes a robust and scalable method that can handle the complexity of real-world driving scenarios, including varying road conditions, speed limits, and driving patterns.

Achieving the mentioned contributions can be broken down into the following steps:

- **Performing a comprehensive analysis of emerging opportunities to improve energy efficiency in FCEVs:** This review explores how upcoming advances in onboard sensors and intelligent driving can offer new tools to reduce fuel consumption. In addition, it examines the powertrain of FCEVs and similar architectures to establish a link between powertrain optimization and energy-efficient driving. Moreover, a wide range of energy harvesting and recovery methods is investigated, with particular focus on their compatibility with FCEVs.

- **Proposing a sequential framework for optimization of speed planning and EMS to improve energy recovery:** First, real-world test data from an FCEV are observed and analyzed. Then, a precise vehicle model is developed based on the experimental data. At the next step, the identified issues related to energy recovery limitations are addressed through sequential optimization of speed planning and energy management.
- **Integrate speed planning and EMS:** To further improve fuel efficiency, speed planning and EMS are combined into a unified optimal control problem (OCP). This OCP avoids simplifications by employing a realistic energy model that accounts for electric motor efficiency, torque-speed limits, and time-related or distance-dependent parameters and constraints, in an offline setting.
- **Enhancing the integrated approach for real-time use and winter driving:** In the final step of this work, the integrated method is enhanced to support online application. The behavior of surrounding vehicles is taken into account to ensure that energy-efficient maneuvers remain safe under real traffic conditions. In addition, since the combination of road slope and slippery surfaces is a critical factor in regions like Quebec, the study is extended to handle this challenge.

Figure 2.1 illustrates the defined goals as a sequence of steps and presents the evolution of the proposed study in alignment with these steps. This visual representation helps clarify how each goal contributes to the overall structure and direction of the research.

## 1.5 Thesis Structure

The rest of this thesis is structured as follows: Chapter 2 discusses the importance of improving energy efficiency in FCEVs and highlights both established and underexplored

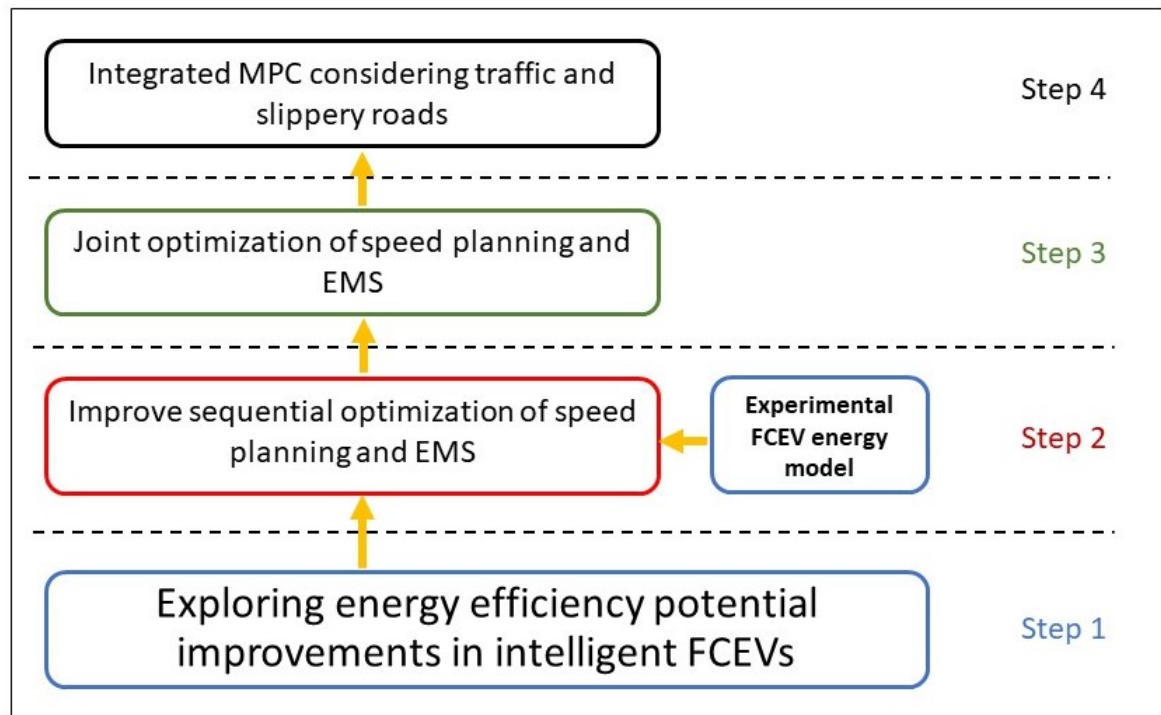


Figure 1.2 Development of the study guided by research objectives

topics related to the connection between energy recovery, energy harvesting, and intelligent driving in new energy vehicles. This will be presented through a review article titled "Energy Recovery and Energy Harvesting in Electric and Fuel Cell Vehicles, a Review of Recent Advances". Chapter 3 begins by explaining what the experimental data reveal about the shortcomings of sequential optimization of EMS and speed, and how these limitations can be addressed. This work is presented as a conference paper titled "The Impact of Dynamic Deceleration Limit on Optimal Speed Planning for Fuel Cell Hybrid Electric Vehicles." The chapter continues by introducing an integrated framework to address the sub-optimal performance of sequential optimization methods. This work is presented in the article titled "Fuel Efficiency Through Co-Optimization of Speed Planning and Energy Management in Intelligent Fuel Cell Electric Vehicles." Chapter 4 explains an integrated model predictive control method designed to enable online

implementation under sloped road conditions and slippery surfaces. This work will be presented in an article titled [title not yet available]. Finally, the conclusion is presented in Chapter 5, along with a detailed discussion of future steps concerning the further improvement of this work.

## Chapter 2 - The Significance of Energy Harvesting and Energy Recovery in New Energy Autonomous Vehicles

### 2.1 Introduction

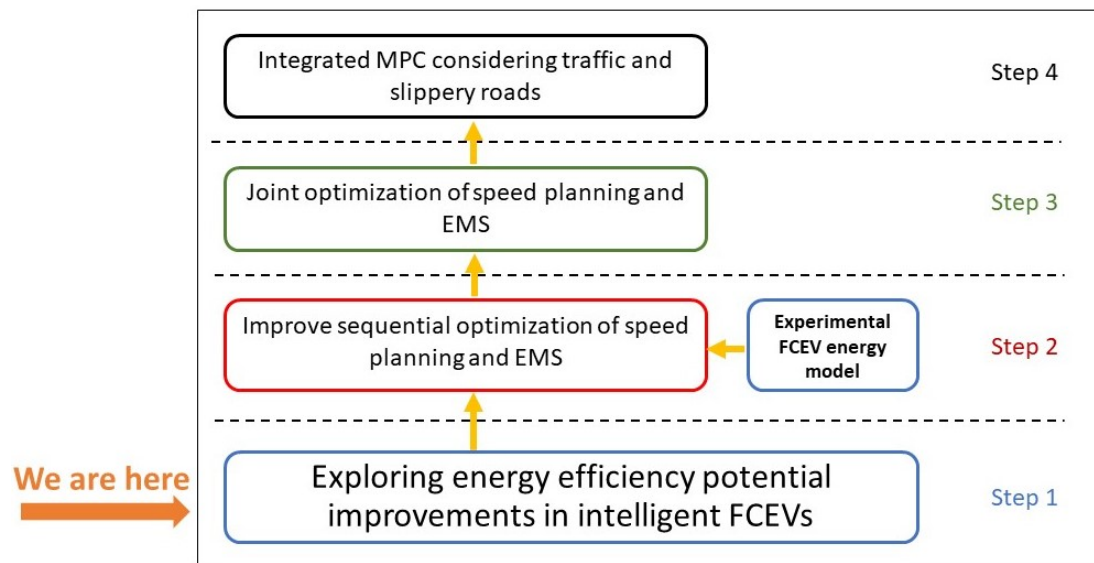


Figure 2.1 The first step in the structure of the presented thesis.

This chapter presents the first article of the thesis, entitled “Energy Recovery and Energy Harvesting in Electric and Fuel Cell Vehicles: A Review of Recent Advances.” The article lays the groundwork by reviewing state-of-the-art techniques for improving energy efficiency and extending driving range. It has two main objectives. The first is to examine how powertrain and vehicle specifications in FCEVs and EVs contribute to energy harvesting and recovery, and help reduce energy losses. The second is to highlight how current advances, such as intelligent driving, can be further developed to improve fuel efficiency and energy recovery. Figure 2.1 shows where this article fits within the overall structure of the study.

First, the article examines powertrain configurations in EVs and FCEVs, followed by an exploration of energy harvesting and recovery methods. The review covers both well-established methods, such as regenerative braking and waste heat recovery, and emerging technologies, including suspension-based and vibration-driven energy harvesting. By examining a wide range of mechanisms and their associated control strategies, this work provides a broad understanding of how various forms of otherwise wasted energy can be captured and reused within the powertrain.

This article plays a central role in the thesis by identifying technical gaps and research opportunities in energy optimization. The insights gained here inform the subsequent chapters, where optimization-based control strategies are developed to improve energy management in FCEVs. In particular, challenges highlighted in this review, such as trade-offs between recovery performance and system complexity, and the limitations of real-time implementation, and the influence of power sources on regenerative braking, have shaped the direction of the original research articles that follow.

## **2.2 Article 1: Energy Recovery and Energy Harvesting in Electric and Fuel Cell Vehicles, a Review of Recent Advances**

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## TOPICAL REVIEW

# Energy Recovery and Energy Harvesting in Electric and Fuel Cell Vehicles, a Review of Recent Advances

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**ABSTRACT** This review article examines the crucial role of energy harvesting and energy recovery in the design of battery electric vehicles (BEVs) and fuel cell hybrid electric vehicles (FCHEVs) as these vehicles have limited onboard power sources. Harvesting energy and recovering energy from onboard systems can significantly improve energy efficiency, increase range, and reduce fuel consumption. The latest advances in vehicular energy recovery and harvesting, including regenerative braking, regenerative suspension, solar and wind energy harvesting, and other recovery methods are studied and the impact of the energy storage system and powertrain architecture on energy harvesting is investigated. Regenerative brake control strategies and driver behaviour's effect on energy recovery are reviewed, and the potential of energy harvesting in electric vehicles is discussed, including experimental and low-power harvesting methods. The importance of using perception and navigation technologies in autonomous vehicles to enhance energy efficiency is highlighted. The article identifies critical research gaps, challenges, and future directions for research in this field. This review stands out from previous papers by covering overlooked subjects such as driver behaviour and deceleration planning in autonomous vehicles, low-power harvesting methods, and experimental techniques applicable to electric vehicles.

**INDEX TERMS** Autonomous vehicles, electric vehicles, energy harvesting, energy dissipation, fuel cell vehicle.

## I. INTRODUCTION

For many years the energy market has been dominated by fossil fuels as the first choice for the transportation industry. However, the fossil fuel shortage and its price, alongside the environmental crisis, have shifted the focus of the automotive industry toward a new generation of vehicles [1]. The recent rise in the EV market in China is a good example of it (Fig. 1). This shift is happening in not only the automotive industry but also in the aerospace and marine industries. This change of trend is in favor of electrical vehicles (EVs). The term EV

refers to vehicles that fully or partially use electric motors for traction. Surprisingly, the idea of employing electric motors to drive a car emerged many years ago. From 1897 to 1900, 28 percent of the total vehicles in the market were of an electric type and were preferred over internal combustion engine (ICE) ones [2]. However, the lower price of oil and the limited range of electric vehicles in that era turned the tide. The reappearance of electrified vehicles in the market was first in the form of hybrid electric vehicles (HEVs) in the 1990s. These vehicles benefit from electric and fossil power sources, for instance, the very successful Toyota Prius model [3]. HEVs combine the drive powers of an ICE and an electrical machine to achieve higher fuel efficiency than

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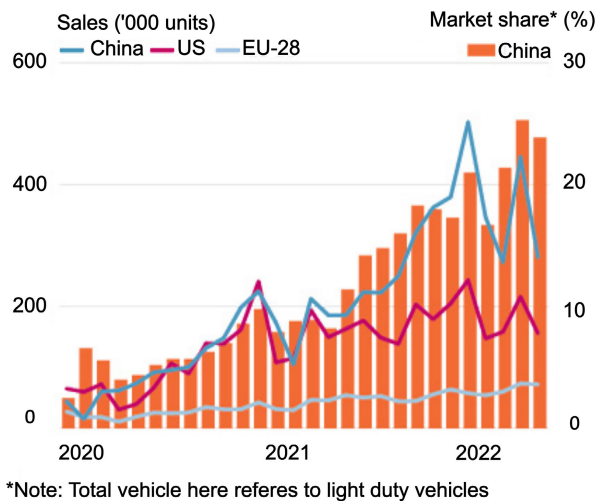


FIGURE 1. The rise in the EV market in China [6].

ICE-only vehicles [4]. There are two basic configurations for the HEV powertrain: Parallel and Series. In the series HEV topology, a generator, driven with ICE provides the electrical power alongside a power storage unit for an electric motor that drives the wheels. In parallel HEV, the power generated by an ICE and an electric motor is merged to drive wheels. In the combined configuration of the HEV powertrain called series-parallel (SP-HEV), the vehicle combines the advantages of both series and parallel configurations, but it has a more complex powertrain and power flow control [5].

In a different classification, HEVs can be classified into four types based on their degree of hybridization: mild HEV, medium HEV, full HEV, and plug-in hybrid electric vehicle (PHEV). Mild HEVs use electricity during stopping and braking events, allowing the ICE to turn off, but do not have a fully electric mode. Medium HEVs can run in fully electric mode for a limited time, in addition, the electric motor (EM) can operate in parallel with ICE. The main difference between a medium HEV and a full HEV is the battery size. Full HEVs have larger battery packs so they can run long distances. PHEV applies both ICE and an electrical powertrain like a normal HEV, but the electric drive acts as the main drive which means PHEVs tend to have batteries with more capacity compared to other HEVs. The difference between PHEV and full HEV is the capability of PHEVs to be connected to the power grid for charging [7].

An EV, that only relies on an electric drivetrain is called a full electric vehicle (FEV). Today battery electric vehicles (BEVs) that only rely on batteries to drive electric motors are very popular. An additional source of electricity can be obtained from a fuel cell which acts as an onboard unit for electricity generation. A fuel cell electric vehicle (FCEV) relies on hydrogen as a fuel with high specific energy to generate electricity and this gives it the advantage of nearly net zero emission [7]. Fuel cell (FC) technology includes different types and among them, proton exchange membrane

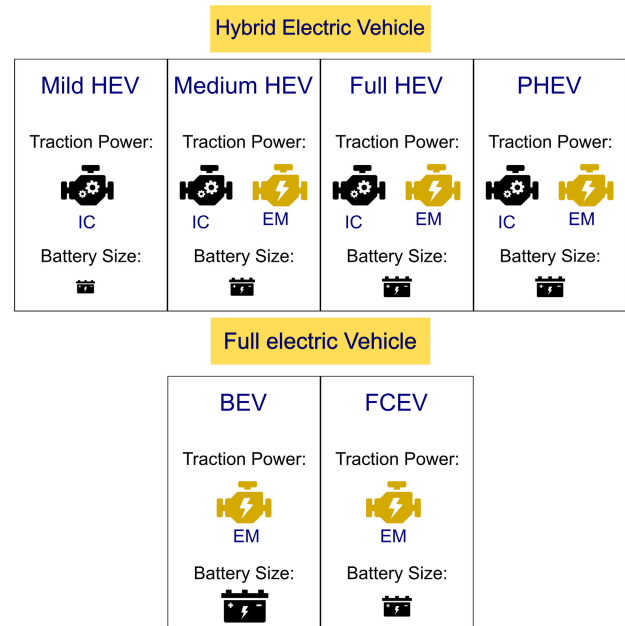


FIGURE 2. The classification based on dedicated traction.

fuel cell (PEMFC) is more promising in terms of applications related to the vehicle industry [8]. In general, a chemical reaction results in ionized hydrogen atoms with a positive electrical charge, and, by providing electrons with a negative charge a current will be produced through the circuit. The produced electricity is used to propel the vehicle or it is stored in an energy storage unit such as a battery or ultracapacitor or a combination of both [9]. It is possible to consider FC as the only source of energy, but it could be applied to only a limited sort of applications, because changing power demand causes problems, for instance, fuel cells should be sized for the maximum power demand [10]. Hybrid energy source facilitates high power demands and store regenerative braking energy, so FCEVs are also called Fuel Cell Hybrid Electric Vehicles (FCHEV) [11]. Table 1 compares different types of EVs. To keep the table as productive as possible some categories are not considered in the table and only widely accepted terminologies are mentioned. Fig.2 shows the classification based on dedicated traction.

Despite the promising prospect of using BEVs and FCEVs on a large scale, there are also other barriers ahead of their widespread application. Considering BEV, the charge station infrastructure is not well-developed yet. This includes a limited number of charge stations, especially in rural areas, and the electric network power shortage in peak hours. Moreover, the charging time of a typical electric car is still much longer than the refueling time of a conventional vehicle. Furthermore, as electric vehicles utilize numerous battery cells with a limited lifetime, the recycling of degraded batteries is an environmental concern. The available resource of Lithium is a controversial topic and while some researchers have indicated insufficient resources for BEV, others have found this claim questionable. Despite these opposing ideas,

**TABLE 1. Characteristics of different EV types.**

| Subgroups of EVs              | Traction Element | Energy Source | Characteristics                        |
|-------------------------------|------------------|---------------|----------------------------------------|
| Hybrid Electric Vehicle (HEV) | Parallel HEV     | EM and ICE    | Battery<br>Ultracapacitor              |
|                               | Series HEV       | EM and ICE    | Battery<br>Ultracapacitor              |
|                               | PHEV             | EM and ICE    | Battery (large)<br>Ultracapacitor      |
|                               | SP-HEV           | EM and ICE    | Battery<br>Ultracapacitor              |
| Full Electric Vehicle (FEV)   | BEV              | EM            | Battery<br>Ultracapacitor              |
|                               | FCEV             | EM            | Fuel Cell<br>Battery<br>Ultracapacitor |

approximately 74 percent of known lithium resources are located in South America and the market is very vulnerable to geopolitical risks [12]. Finally, the limited range is one of the most critical obstacles for BEVs.

FCEVs have some advantages over BEVs, for instance, it only takes 3-5 minutes to refuel a FCEV which is significantly quicker than BEVs and satisfies customer needs for normal applications [13]. Nevertheless, there are even more challenges compared to the BEVs. Fuel cell low durability is a major consideration since current commercial FCEVs offer a fuel cell life span that is considerably lower than other competing technologies. The high cost of fuel cells and hydrogen is another barrier to the widespread use of these vehicles. The majority of hydrogen production relies on the hydrocarbon reforming process [14]. So, in terms of cost-per-kW, it is more expensive than the direct use of fossil fuel and without a renewable source, it is not clean energy. In addition, hydrogen refueling infrastructure and storage systems are the bottlenecks for its fast development [15]. Lastly, the slow dynamics of the fuel cell limit the characterization of the system.

To tackle these problems a wide variety of solutions are investigated in the scientific community. One solution would be a photo-voltaic hybrid electric vehicle (PVHEV) that uses solar energy to charge batteries. However, PVHEVs are still in the developing phase [4] and are inefficient in areas with low sunlight. Investigating new battery chemistry to maximize energy density has been an attractive field for many studies [16], [17], [18], [19], [20], [21]. In addition, research regarding optimizing the fuel cell stack is an answer to overcome fuel cell-related shortcomings [22], [23], [24], [25]. Besides, the optimization of energy management contributes

to facilitating the implementation of BEVs and FCEVs [26], [27] [28]. Recovering the dissipated energy in vehicles is an efficient approach to decreasing energy consumption in BEVs and FCEVs.

To have a better understanding of energy harvesting advantages, it is necessary to break down the energy usage in an EV. To measure energy loss and use in an EV, it is important to consider the vehicle type, because these factors may vary from one vehicle to another. Furthermore, different driving patterns can affect energy requirements in an FEV. Despite these varying numbers, a general idea about energy flow can be illustrated. When a vehicle moves due to friction and air drag, it dissipates energy. Also, when a vehicle is turned on there is a minor power use for applications like controls, dash lights, etc. For an EV driving on a highway energy loss in an electric drive system is 15 percent, 5 percent less than an EV in stop-and-go drive cycles. Energy loss in accessories on the highway is 2 percent compared to 4 percent in the city. Auxiliary electrical devices are responsible for 0 percent to 2 percent of energy loss on the highway and 0 percent to 6 percent in the city. Finally, 71 to 73 percent of the energy is delivered to wheels on the road. This number is approximately 60 to 66 percent for an EV in stop-and-go scenarios [29], [30], [31], [32], [33]. Fig.3 illustrates the average dissipated and used energy in an EV based on the drive cycle.

Harvesting and recovering energy can be implemented in various types of transportation, including marine vessels, UAVs, trains, and vehicular applications. However, the challenges and opportunities to harvest and recover energy in each type of transportation vary. In the automotive context, energy can be obtained through different methods such as

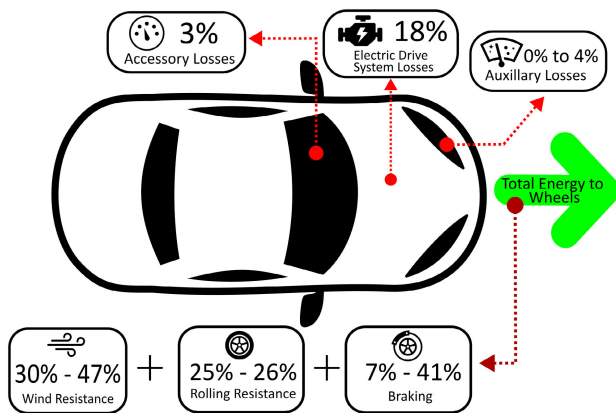


**FIGURE 3.** Energy loss in the electric vehicle based on city and highway driving cycles based on the data provided in [29], [30], [31], [32], and [33].

regenerative braking, regenerative suspension, solar harvesting, RF energy harvesting, and more. One crucial aspect of energy harvesting and recovery systems is their compatibility with established protocols and industry guidelines. These guidelines comprise safety standards, durability, reliability, and ride comfort. In this paper, the possibility and the amount of available energy to harvest energy marks regenerative braking as the most promising source, and a comprehensive review of strategies and challenges regarding regenerative braking will be presented. Moreover, a short review of other harvesting potentials will be carried out. In the majority of published review papers, the differences between FCEV and BEV are not taken into account as they apply different energy management strategies. In addition, the battery size in FCEV and BEV are not the same and this makes a huge difference in the ways they use the harvested energy which will be explained in the next sections.

#### A. SEARCH STRATEGY AND ARTICLE SELECTION

To conduct a comprehensive review of energy harvesting and energy recovery in BEVs and FCEVs, electronic databases were searched using specific keywords. Articles older than 2010 were excluded (note that some references older than this date have been used in this article for general explanations). The selected studies focused on EVs and FCEVs, or their findings were applicable to these vehicle types. The process and criteria for selecting references are illustrated in Fig. 4. Although topics such as heat energy recovery or aerodynamic design of vehicles were related to the scope of this review paper, they have been excluded due to extensive previous studies and their similarity to both conventional and alternative fuel vehicles.

#### B. CONTRIBUTIONS

Several works have been done on energy harvesting in vehicles. However, to the best of the authors' knowledge, no comprehensive study has been carried out in this regard which mainly focuses on BEVs and FCEVs. Hybrid vehicles

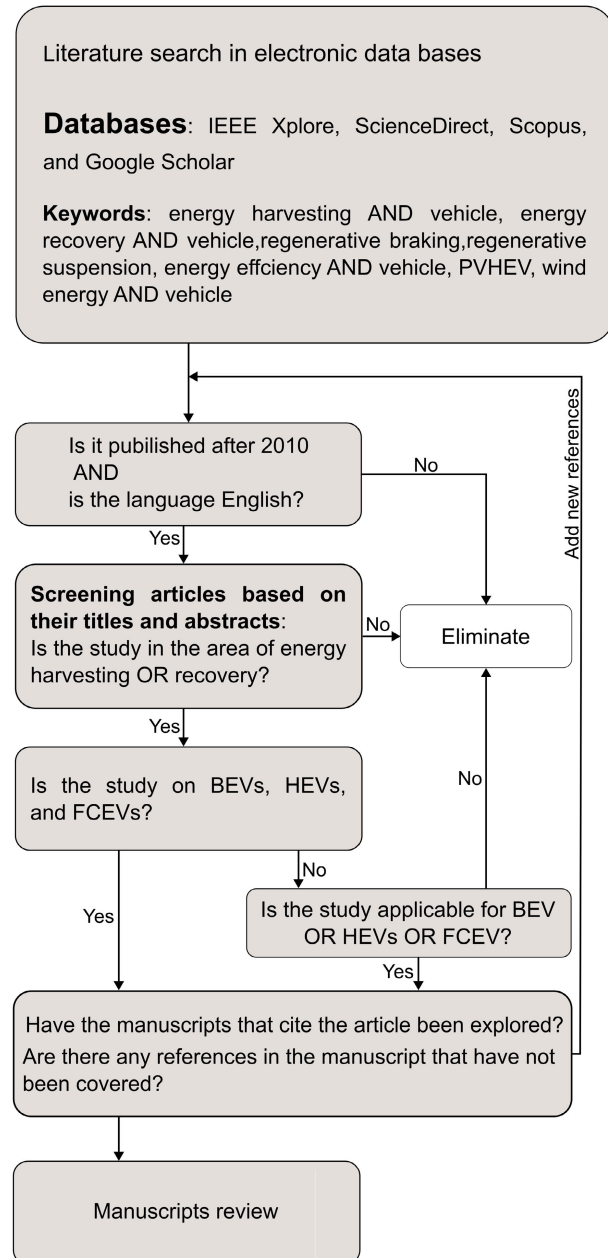


**FIGURE 4.** The process of selecting references.

include an IC which converts only the friction of fuel energy to useful work and the rest is lost as heat. There are various approaches for recovering heat from IC and it has been already studied in numerous works. In this paper, we are not covering IC heat recovery, and readers are referred to existing research. Excluding ICE and thermal energy recovery (TER) helps this review in two steps. First, it allows us to look deeper at the relationship between EVs architecture and energy harvesting. And second, we can focus on more recent energy recovery methods. For instance, in recent years there is an increasing trend toward energy harvesting in autonomous EVs. Covering energy harvesting in autonomous BEVs and FCHEVs is another difference between the proposed study

and similar works. In addition, the impact of human drivers' behaviour and autonomous navigation on energy harvesting is presented. Moreover, the methods of low-power energy harvesting such as radio frequency energy harvesting or rim-mounted devices are presented. Table 2 compares recent related review papers with this review.

### C. THE STRUCTURE OF THE REVIEW

Before investigating the potential sources for energy harvesting, there will be a review of the energy storage systems in EVs and the related architectures in BEVs and FCEVs. Covering energy harvesting methods begins with regenerative braking considering different influential factors such as control strategy and inputs, driver behaviour, and autonomous driving. It follows with a review of energy harvesting in the suspension system and specific applications in EVs. In the next section solar, wind, and other harvesting methods are analyzed. Finally, current challenges and gaps are mentioned.

## II. FEV ARCHITECTURE

The powertrain architecture of FEV may include batteries, ultracapacitors, fuel cell stacks, converters, and inverters. The combination of these parts results in different architectures and developing a deeper understanding of them helps to realize energy loss in FEV.

### A. BEV ENERGY STORAGE SYSTEM (ESS)

The ESS of a BEV may include a battery, UC, or both and it may contain different types and numbers of DC converters.

#### 1) BATTERY

There are various types of batteries available and widely accepted in the market: Lead-acid batteries, Nickel-Cadmium (NiCd), Nickel-Metal-Hydride (NiMH), Lithium-ion (Li-ion), Lithium-ion Polymer, and Sodium Nickel Chloride (NaNiCl) [40].

##### a: LEAD-ACID

Lead-acid batteries are the earliest form of battery technology and are still widely used today due to their low cost of production and impressive power-to-weight ratio. However, when it comes to batteries for use in fully electric vehicles (FEVs), lead-acid batteries may not be the best choice. This is because FEV batteries need to be able to operate at a partial-state-of-charge (PSOC) in order to efficiently accept rapid charging, something that traditional lead-acid batteries are not designed to do [41]. As a result, the energy harvesting capacity of these batteries can be reduced, making them less than ideal for use in FEVs.

##### b: NiCd

This technology has also been around for more than a century. Its long-life cycle sounds promising in terms of use in the FEV industry, but it has low energy density. More importantly, it contains a highly toxic element of cadmium [42]. It can cause environmental problems and

threats to all living organisms, even in very low amounts. These issues indicate that its usage will be limited in many applications including FEVs [43].

##### c: NIMH

NiMH battery is capable of rapid charge which is an interesting feature for EVs. Being maintenance-free and having long life makes it a typical choice for HEVs including PHEVs [44]. However, their storage capacity is lower than Li-ion batteries and they are more expensive compared to lead acid batteries.

##### d: LI-IO

Li-ion batteries first appeared in 1985 and six years later they were commercially available. These batteries have a high energy storage capacity and considerable energy density, also Like NiMH, they are capable of rapid charging. Currently, the ESS market for FEVs is dominated by li-ion technology [45]. The other important characterization regarding Li-ion batteries is the low self-discharge rate and a wide range of operating temperatures.

##### e: LITHIUM-ION POLYMER

With its higher energy density, this battery technology has quickly gained popularity in the portable electronic device market and has even surpassed other types of batteries in terms of usage. However, despite these benefits, certain factors have prevented its widespread application in larger-scale implementations, such as in fully electric vehicles (FEVs). Safety issues, as well as concerns surrounding the overall cell life and performance of these batteries, have hindered their adoption in this context [46]. Nevertheless, efforts are underway to address these issues and explore the potential of this technology for broader applications.

##### f: NaNiCl

These batteries also referred to as Zebra battery has been reported as the best choice regarding energy consumption since they have a high energy density [47] but the current problem in terms of operational safety is stopping them from being widely used.

#### 2) ULTRACAPACITOR

Ultracapacitors (UC) are energy storage units that store energy without any chemical reactions. Therefore, they have a long-life cycle and higher power density compared to batteries. This makes UC a good candidate for capturing regeneration braking energy in EVs as they are capable of quickly capturing and delivering electric energy peaks. However, they suffer from a high discharging rate and low energy density. These characteristics affect their effectiveness choice as the sole component in an ESS. On the other hand, batteries have a high energy density and a hybrid energy storage system (ESS) including the combination of

**TABLE 2.** Comparison between the presented review and recent related reviews.

| Review papers              | Year | Cover regenerative braking | Cover regenerative suspension | Focus on BEVs | Focus on FCEVs | Considering autonomous vehicles | Driver impact on energy recovery | Solar and harvesting | Wind and harvesting | Experimental low-power harvesting | Considering energy storage system |
|----------------------------|------|----------------------------|-------------------------------|---------------|----------------|---------------------------------|----------------------------------|----------------------|---------------------|-----------------------------------|-----------------------------------|
| [34]                       | 2021 | ✓                          | ✓                             | ✓             | ✗              | ✗                               | ✗                                | ✓                    | ✓                   | ✗                                 | ✗                                 |
| [35]                       | 2021 | ✓                          | ✓                             | ✗             | ✗              | ✓                               | ✓                                | ✗                    | ✗                   | ✗                                 | ✗                                 |
| [36]                       | 2018 | ✓                          | ✗                             | ✗             | ✗              | ✓                               | ✓                                | ✗                    | ✗                   | ✗                                 | ✗                                 |
| [37]                       | 2018 | ✓                          | ✓                             | ✗             | ✗              | ✗                               | ✗                                | ✗                    | ✗                   | ✗                                 | ✗                                 |
| [38]                       | 2022 | ✓                          | ✓                             | ✓             | ✗              | ✗                               | ✗                                | ✗                    | ✗                   | ✗                                 | ✓                                 |
| [39]                       | 2021 | ✓                          | ✓                             | ✗             | ✗              | ✗                               | ✗                                | ✗                    | ✗                   | ✗                                 | ✓                                 |
| The presented review paper | –    | ✓                          | ✓                             | ✓             | ✓              | ✓                               | ✓                                | ✓                    | ✓                   | ✓                                 | ✓                                 |

batteries and UCs is very promising in terms of designing a well-rounded ESS for EVs with greater efficiency [4], [48].

### 3) BEV ARCHITECTURES

An ESS only consisting of a battery results in two architectures: the battery is directly connected to the AC inverter, or it is connected to the DC converter, and the converter is linked to the inverter. In the former architecture, the DC-link voltage varies greatly but in the latter one, the bidirectional DC/DC converter controls the power flow [49]. The combination of the battery and UC results in different configurations which are: Passive parallel, fully active, and semi-active. The semi-active configurations are UC/battery and battery/UC, and the fully active configurations are cascade (series), parallel, and multiple input converter configurations. Fig.5 shows different hybrid ESS configurations. The passive parallel configuration is very simple and since there is no control between two units the utilization of UC is not completely effective [50].

Regarding the semi-active configurations, in UC/battery configuration the DC/DC converter is interfaced with UC, and the battery is connected directly to the DC link. In this setup, the battery is protected yet, but the UC operates inefficiently. In battery/UC configuration the direct connection of UC to the DC link results in the working of UC as a low pass filter and the DC link voltage is allowed to vary [51].

In fully active configurations decoupling UC and battery leads to more accurate control. In the cascade or series topology stabilizing the terminal voltage of the battery pack is simpler. In parallel fully active topology, the battery and UC are connected to the DC bus with separate bidirectional DC/DC converters that grant considerable flexibility. The multiple-input converter configuration decreased the cost of parallel while maintaining the separate control of the battery and UC [52].

As it was mentioned the control advantage of applying a converter comes with the cost of energy loss, which can happen during spending or harvesting the energy. Considering the energy architecture of the EV or FCEV we

can employ strategies that minimize energy loss. For instance, for vehicles with hybrid energy sources, it is beneficial to limit the number of occasions on which the IC or FC charges the ESS and should rely on energy harvesting to do so.

### B. FC AND ENERGY STORAGE SYSTEM ARCHITECTURE

To highlight the different approaches regarding BEV and FCEV, it needs to have a deeper look at FCEV and the different architectures studied in the literature as they are in the early phase of development [53].

#### 1) FUEL CELL

The characteristic of FC is ideal for providing constant power in applications like forklifts, submarines, and buses which are considered slow-speed vehicles [54]. FC has slow dynamics, and it is also affected by other factors like temperature and fuel delivery system performance. Therefore, it cannot satisfy rapid load demands without voltage drop known as the fuel starvation phenomenon. Consequently, it is necessary to have an auxiliary power source to help with peak power and store harvested energy [55]. Based on that, FC acts as the main source of energy for the vehicle, and another auxiliary source, that is capable of delivering and storing extra power is also used. Batteries and ultracapacitors are the most common ones in FCEV and different configurations of these sources have been studied in the literature.

The combination of FC, battery, UC, and DC/DC converter results in six topologies that have been studied in the literature [28], [54] [56]. Fig.6 depicts these topologies. Direct use of both FC and ESS without a DC/DC converter (T2) is not common in vehicles because ESS and FC must operate at the same voltage, this setup is used in aircraft applications [57]. Other topologies are suitable for vehicular applications but the mainstream design for most FCEVs is the combination of fuel cell and battery (T2 and T4 in Fig.6) [58]. Topologies including both battery and UC suffer from losses of power flow and as a result, they are complex in terms of control, but it has been reported that they have the highest energy conversion efficiency among others [59].

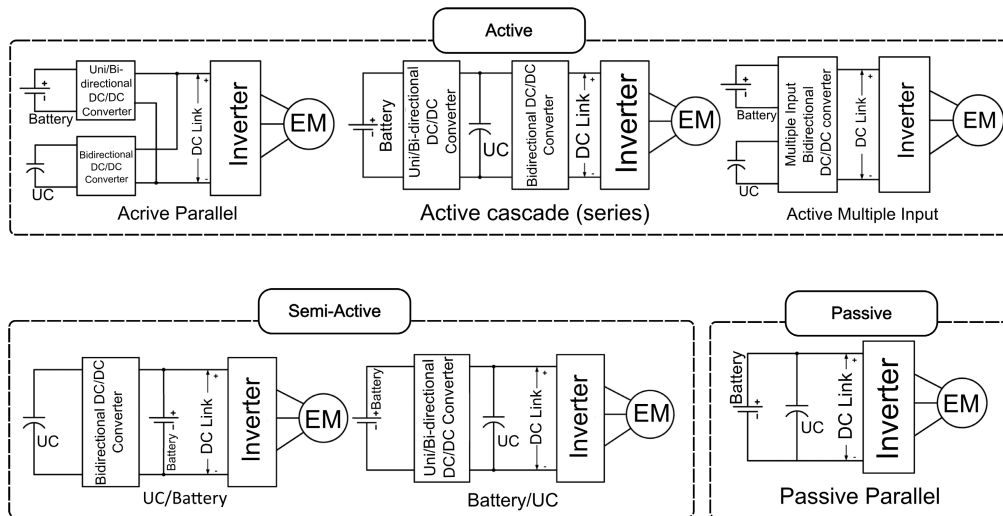


FIGURE 5. Hybrid ESS configurations in EVs [51].

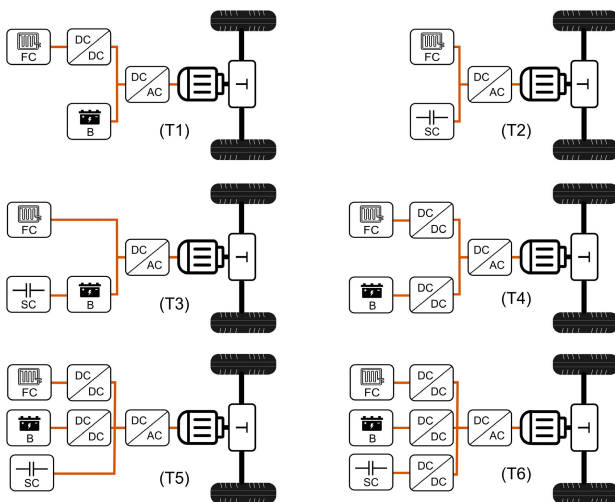


FIGURE 6. Different architectures of FCEVs [56].

## 2) DIRECT AND INDIRECT

Although the mentioned topologies cover all configurations, many studies have preferred to categorize the hybridization of FCEVs into direct (passive) and indirect (active) classifications [60]. The key difference between these two classifications is the use of DC/DC converters for the FC system. In the direct configuration, FC is connected to the DC bus or battery with a direct link while in the indirect type, FC (or ESS) firstly is connected to the unidirectional DC/DC converter, and then it connects to the DC bus alongside the ESS [27].

DC/DC converters shift the level of voltage in addition to stabilizing their output with unstable input. In the FC, it increases the voltage level from the fuel stack output to the voltage available at the DC bus. Based on the high voltage and low voltage demand, different DC/DC converters are used

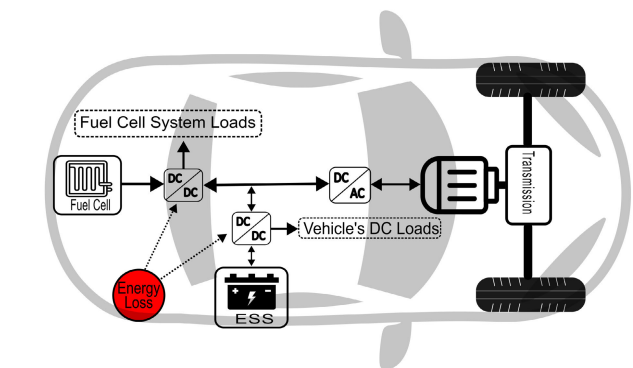


FIGURE 7. The most common architecture of FCEV and energy loss in converters.

in an EV or FCEV and a DC/AC inverter converts the DC input into three phases of voltage suitable for the EM [61]. The direct type offers low power loss and lower cost due to removing a DC/DC converter but as it was mentioned the operation procedure is very limited as discrepancies in the voltage-current behaviour of FC and ESS may occur [62]. Implementing a high gain converter in the indirect type gives control and is the best solution to the problem of low voltage and high current of FCs but the trade-off is energy loss at voltage converters [60]. Fig.7 shows the structure of indirect hybridization indicating the energy loss in the most common configuration in FCEVs. The DC/DC converter connected to the ESS is bidirectional, so in the occasion of capturing the braking energy, it can be used to charge the battery during cold start or high-power demand it supplies the system.

It is noteworthy to mention plug-in fuel cell electric vehicles (PHFCEV or PFCEV) that apply FC and battery hybridization. PFCEVs have a battery with a higher capacity to run on pure battery mode for a longer time and they can

be charged from the electric grid similar to conventional PHEVs mentioned before [63]. The combination of hydrogen fuel cells and BEVs offers many benefits as it facilitates the refueling process but a more complex design is required [64].

### III. REGENERATIVE BRAKING

Based on the information provided in Fig.3, the major part of the energy is directed to the wheels to accelerate the vehicle and drive at a desirable speed. A moving vehicle's energy is lost by a considerable amount during the process of braking. The kinetic energy is converted to heat between the brake pads and the wheel. In cities with heavy traffic, more than half of the energy is dissipated in stop-and-move patterns [65]. Recapturing this wasted kinetic energy is the main idea of regenerative braking. During the regenerative braking process, the EM acts as a generator and produces a negative torque on the wheels. In this way, part of the kinetic energy is converted to electrical energy stored in the ESS [66]. Fig. 8 depicts the process of regenerative braking. The EM is not the only means to conserve energy and a hydraulic pump motor can also be used to store energy in a high-pressure accumulator. The flow between a low-pressure accumulator and a high-pressure accumulator can apply the stored energy for driving the vehicle in time of demand [67].

The longitudinal vehicle dynamic can be used to present the amount of regenerative brake power. According to Newton's second law of motion:

$$m \frac{dv}{dt} = F_T(t) - F_{res}(t) - F_b(t) \quad (1)$$

In this equation,  $m = m_0 + m_r$ , is the total effective mass, including the total sum of the vehicle's mass,  $m_0$ , and  $m_r$  which shows the inertia of all rotating parts.  $F_T$  is the traction force, and  $F_b$  is the applied braking force.  $F_{res}$  represents the road loads and it can be shown as [68]:

$$F_{res} = mg(\sin\theta(s(t)) + C_{rr}\cos\theta(s)) - \frac{\rho_a A C_D v(t)^2}{2} \quad (2)$$

In the given equations, various factors contribute to the overall resistance experienced by the vehicle. These include the coefficient of rolling resistance,  $C_{rr}$ , the road slope represented as a function of position  $s$ , denoted by  $\theta$ , the vehicle's front area, represented by  $A$ , the drag coefficient, denoted as  $C_D$ , the air density, denoted as  $\rho_a$ , and the vehicle speed, represented as  $v(t)$ . Additionally, the cornering resistance can be expressed as  $C_r \frac{m^2 v(t)^4}{R(s(t))}$ , where  $R(s(t))$  represents the radius of curvature out of the plane of the image, and  $C_r$  represents the cornering coefficient. However, the cornering resistance is usually considered negligible due to the relatively small magnitude of  $C_r$ , which is typically on the order of  $10^{-5}$  [68].

The total braking force ( $F_b$ ) is comprised of friction braking force and regenerative braking force as shown in equation 3 [69]:

$$F_b = F_{Frc} + F_{Rgn} \quad (3)$$

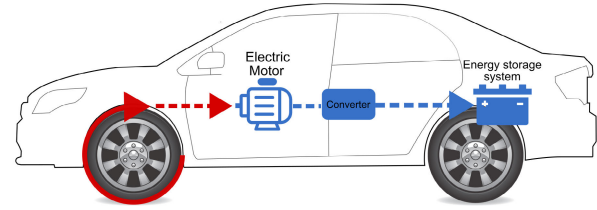


FIGURE 8. Regenerative braking in an EV.

Several factors affect regenerative braking, including the vehicle's mass, speed, road slope, air resistance, rolling resistance, and the allocation of friction brakes. The electric power delivered to the EM or generated during regenerative braking,  $P_m$ , is a function of motor torque ( $T_m(t)$ ) and rotational speed ( $\omega_m(t)$ ) as it is shown in equation 4. It is generally tabulated as the EM efficiency map or "motor map" [68]:

$$P_m = f(T_m(t), \omega_m(t)) \quad (4)$$

There are a variety of configurations for the drivetrain of EVs. In a simplified model we can assume that the EM and wheels are connected through a transmission with a fixed ratio  $g_0$ . The rotational speed and torque of the wheels can be calculated as:

$$T_w = g_0 T_m \quad (5)$$

$$\omega_w = \frac{1}{g_0} \omega_m \quad (6)$$

The motor map depends on the type of machine. Fig.8 depicts an example of a motor efficiency map. based on the reversible application of EM, it can operate as a motor ( $T_m > 0$ ) or as a generator ( $T_m < 0$ ). The battery power,  $P_b$ , can be shown as  $P_b = V_c I_c$ , where  $v_c$  and  $I_c$  are the charging voltage and charging current of the battery respectively. In the regenerative mode, the relation between the charging power of the battery and the motor power can be described as motor-to-battery regenerative efficiency  $\eta$ , which is shown in equation 7 [70].

$$\eta = \frac{V_c I_c}{T_m \omega_m} \quad (7)$$

#### A. ENERGY STORAGE SYSTEM FOR REGENERATIVE BRAKING

ESS plays a principal role in regenerative braking. The possibility of using the recaptured energy depends on ESS and it is important to consider its limits to maximize the harvested energy. Storing the braking energy in a high-pressure accumulator in refuse collection vehicles and buses has been investigated [72], [73]. A combination of a hydraulic drive system and a braking strategy is reported to be effective regarding energy regeneration [74]. In other types of energy storage systems, like the spring energy storage system, the kinetic energy during the braking process is stored in

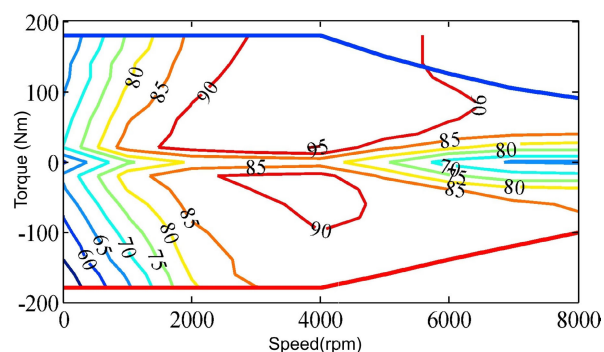


**FIGURE 9.** Example of EM efficiency map [71].

a compressed spring and the potential energy of the spring converts back into kinetic energy when required. Hydraulic energy storage systems, spring energy storage systems, and flywheel energy storage systems that store the kinetic energy of a rotating flywheel have been discussed comprehensively in the literature [38]. Since this paper's focus is on FEVs, the focus is on batteries and ultracapacitors which have shown high efficiency in this type of vehicle [75]. Table 3 presents a comparison of various ESS utilized for capturing regenerative brake energy. The table provides examples of references that have applied these ESS.

As it was mentioned before, batteries are the most common form of ESS in FEVs and play a significant role as the regenerative braking generates a high power as it is active. Battery capacity which is shown and measured in ampere-hours (Ah), voltage level, and battery power vary based on the different types of battery. The other important factor in batteries is the state of charge (SOC) which is very important in the process of regenerative braking. For all types of batteries and in particular lead-acid batteries, SOC strongly affects charge acceptance which is a significant factor during regenerative braking [87]. Besides the SOC, the other challenge for regenerative braking regarding batteries is temperature. These two factors strongly impact the FEV's ability to harvest braking energy.

Li-ion batteries have a wide range of operational temperatures but in fact, considering charging operations, there is a major obstacle that deeply affects battery function and hence energy harvesting. Low temperature causes several issues for Li-ion batteries and regarding energy harvesting capability; reduction in the available energy of the battery is the main problem [88]. This issue limits the energy harvesting potential in countries with many sub-zero temperature days, for example, Canada, Norway, and Russia. The application of lithium-ion batteries in cold weather has been reviewed in the literature comprehensively [89]. Battery preheating strategies, as a solution for FEVs in cold temperatures, have been reviewed in the literature [90]. In [91], a novel approach has been suggested to harvest braking energy not only to charge the battery but also to heat the battery. A control strategy was applied to activate the self-heating of Li-ion batteries during braking and rest intervals in driving.

For the batteries with smaller capacity, the ability to recapture the energy is limited and this is the case in the FCEVs as the charging current is also limited. Toyota Mirai and Hyundai Nexo are two commercially available FCEVs in the market, Mirai has a battery capacity of 1.2 kWh and Nexo has a 1.6 kWh battery. These numbers are considerably lower than the battery capacity of BEVs, for example, the Tesla Model 3 has a 60 kWh battery pack. Many researchers have assumed batteries with large capacity in their research, close to BEV's capacity. In [92], 25 kW was considered to design a fuzzy logic power management strategy for an FCEV. In [93], an energy management system (EMS) has been proposed to improve fuel economy in an FCEV having a battery with a capacity of 38 kWh, furthermore, a 13 kWh battery was part of the model specification in [94] where a sub-optimal EMS was studied on FCEV.

It is worth mentioning that the effect of energy harvesting in the brake system in Li-ion batteries has been investigated and no detrimental effect on battery life has been reported [95]. In fact, as limiting the depth of discharge extends the battery life [96], regenerative braking supports longer battery life. In section II, the benefits of hybrid ESS were covered. In [97], a hybrid energy storage system (HESS) of battery and ultracapacitor with a switching algorithm is used to provide a simple and highly efficient method for energy regeneration of brakes. The method is reported to improve efficiency by about 20 percent. Also, a HESS has been tested alongside a multi-object optimization problem to extend the battery life [98]. In [99], the effect of using UC in HESS in FCEVs has been explored and it was found that the use of UC increases the performance to recapture more kinetic energy of FCEV during a braking event. In the mentioned research, the application of batteries with low capacity in a commercial FCEV was considered.

From a safety standpoint, proper maintenance and regulation of ESS (Energy Storage Systems) is crucial. It involves managing charging capacity, temperature, SOC (State of Charge), and state of health. Poor control of these parameters can hinder RBS (Regenerative Braking Systems), harm the ESS, and vehicle and passenger safety. Fire accidents in the formula one vehicle with regenerative braking and electric ESS is an example of it [38].

## B. REGENERATIVE BRAKING CONTROL STRATEGY

Electric vehicles with regenerative braking systems are also equipped with conventional friction brakes and based on this configuration there are three states during the braking process:

### 1) FIRST

EV may only depend on regenerative braking to stop, and all the braking energy is recaptured. In this case, the friction brake is not used. when the demand for deceleration is not high and immediate, vehicles could operate in this state.

**TABLE 3. Various ESS for regenerative braking system.**

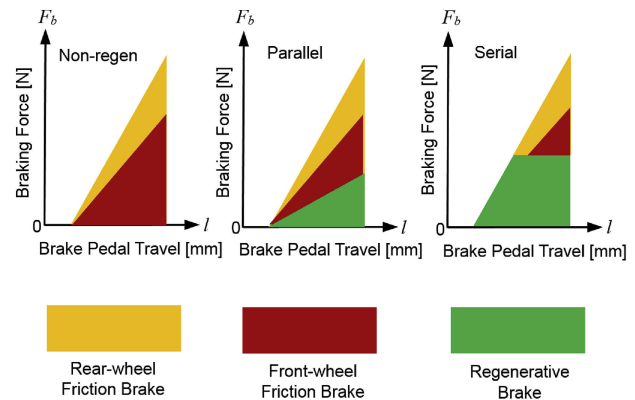
| Type of ESS               | References       | Advantage                                                                                                                                             | Disadvantage                                                                                                                                                                                                                                                                                                  |
|---------------------------|------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Battery                   | [76], [70], [77] | <ul style="list-style-type: none"> <li>• High energy density</li> <li>• Already available for BEVs and FCHEVs</li> <li>• Mature technology</li> </ul> | <ul style="list-style-type: none"> <li>• Limited charging current</li> <li>• Pollution from battery</li> </ul>                                                                                                                                                                                                |
| UC                        | [78], [79], [80] | <ul style="list-style-type: none"> <li>• Fast response and charging</li> <li>• High power density</li> </ul>                                          | <ul style="list-style-type: none"> <li>• Some complex mechanical parts are replaced since the wheels are driven by an EM</li> <li>• Smaller and more efficient ICE that acts as a generator</li> <li>• Conversion of energy from electrical to mechanical reduces the overall system effectiveness</li> </ul> |
| Flywheel                  | [81], [82], [83] | <ul style="list-style-type: none"> <li>• High energy density</li> <li>• Eco-friendly</li> </ul>                                                       | <ul style="list-style-type: none"> <li>• Heavy weight and needs extra space</li> <li>• Not possible to save energy for long periods</li> </ul>                                                                                                                                                                |
| High-pressure accumulator | [72], [73], [74] | <ul style="list-style-type: none"> <li>• High power density</li> <li>• High charging and discharging rate</li> </ul>                                  | <ul style="list-style-type: none"> <li>• Need space, not suitable for passenger vehicles</li> <li>• Heavy weight</li> </ul>                                                                                                                                                                                   |
| Spring                    | [84], [85], [86] | <ul style="list-style-type: none"> <li>• No energy loss in conversion</li> </ul>                                                                      | <ul style="list-style-type: none"> <li>• Complex mechanism</li> <li>• Heavy weight</li> <li>• Limited energy recovery</li> </ul>                                                                                                                                                                              |

## 2) SECOND

EV uses both friction and regenerative braking simultaneously and each brake has a different share of total braking force which is called blending. Regarding blending, there are two classifications, serial, and parallel [100]. In parallel regenerative braking, both brakes are applied simultaneously. In serial regenerative braking, brake force is generated by regenerative braking unless the needed brake force exceeds a particular point [101]. Fig. 10 shows different classifications of braking and their effect on energy harvesting in a vehicle with only friction brakes on the rear wheel and both friction and regenerative brakes on the front wheel. In the serial, friction brakes on the rear and front wheels are applied when the required braking force exceeds a specified force.

## 3) THIRD

EV only applies friction brake to stop the car. The emergency stop is one reason for this braking scenario because of insufficient resistance torque produced by EM. With fully charged batteries also there is no need for harvesting braking energy. In addition, at low speeds, it is a challenging task for EM to act as a generator, therefore a low-speed threshold is considered, and at speeds below that, regenerative braking is inefficient and also harms the total performance of an EV [103]. The low speed in literature is considered 10 km/h and should be considered as a barrier to energy harvesting [104], [105].

**FIGURE 10. Serial and parallel regenerative braking [102].**

From this perspective, energy harvesting efficiency is influenced by the control strategy employed to decide the allocation of regenerative and friction braking. A reliable control strategy is needed to guarantee the safety and stability of the vehicle in braking events and maximize regenerative braking. In addition, driving comfort is another important factor that should be considered alongside braking performance and energy recovery rate [106]. Stability, safety, and energy recovery can be considered the main goals of a regenerative braking system (Fig.11).

Different control strategies and controllers have been investigated in the literature [7], [38], [107], [108], [109].

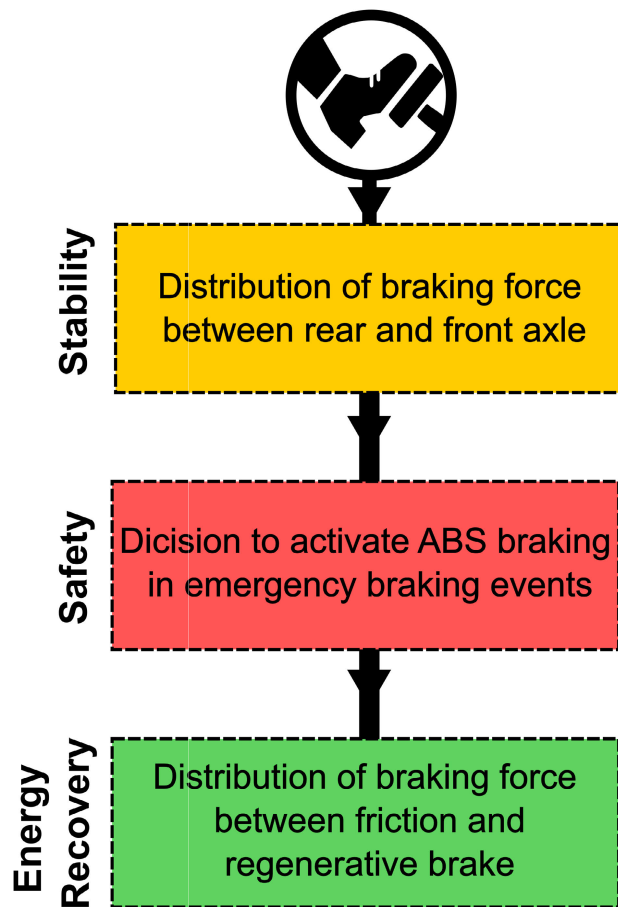


FIGURE 11. Main goals in the regenerative braking system.

The most common classification is by considering employed controllers and thereby fuzzy logic controllers, sliding mode controllers, PID controllers, neural network controllers, model predictive controllers, supervisory rule-based control, multi-layer controllers, and other methods are discussed.

#### 4) REGENERATIVE BRAKING IN A CONVENTIONAL HEV AND BEV

Based on The National Highway Traffic Safety Administration (NHTSA), autonomous vehicles are defined in levels from 0 to 5. In level 0 the human driver has full control of the vehicle and in level 5 the vehicle is completely independent for driving which is called full automation. In level 1, acceleration, braking, and steering are assisted by the system driver is fully in control of the vehicle. Additional features like highway pilot are the difference between level 1 and level 2. In level three, the vehicle can perform a driving task, but the driver should be ready to get engaged. Level 4 is similar to level 5 but the service area in level 4 is limited [110]. Today conventional EVs belong to levels 1 and 2. Level 3 vehicles are emerging and research on upper levels is an interesting and popular topic for researchers. In this paper, conventional electric vehicles refer to levels 1 and 2.

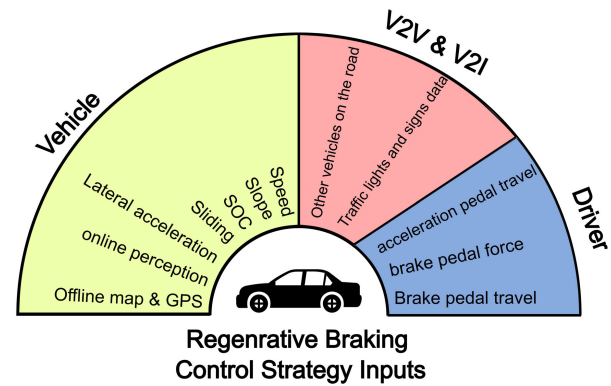


FIGURE 12. Different inputs of a regenerative braking control strategy.

The basic input for the control strategy of regenerative braking is signals from the brake pedal. A human driver creates this signal by the pedal travel and the force he applies to the pedal which results in the calculation of the requested brake force and the activating anti-lock system, if applicable. As it was mentioned before, the SOC of the battery is an important characteristic during regenerative braking. In addition, there are many other inputs from different sensors that have been applied, for instance, speed, the slope of the road in real-time, feedback from hydraulic brakes, etc [108]. The three most frequent factors for the control strategy are brake pedal force, speed, and SOC [111]. Fig. 12 shows different inputs that can be considered to design a regenerative braking control strategy.

In [112], a regenerative braking control strategy based on fuzzy logic control was proposed, considering inputs such as required braking force, vehicle speed, and SOC. The output was regenerative braking allocation in total braking force, leading to increased vehicle system efficiency. Lv et al. [113] studied a similar control strategy for an HEV with the EM on the rear axle, where the fuzzy controller determined the share of regenerative brake force in the total braking force. Xu et al. [114], [115] applied the same approach to a four-in-wheel motors EV, considering SOC, brake force, and vehicle speed as inputs. Saradaleshmi and Binojkumar [116] utilized SOC, brake force, and vehicle speed as inputs for their fuzzy controller in a BEV, with the output serving as the input for a PI controller. Ko et al. [117] introduced cooperative control of regenerative and friction braking force allocation by considering pedal stroke, gear step, and vehicle step. Xiao et al. [118] integrated brake strength, SOC, and motor speed into their fuzzy logic controller, considering emergency situations with mechanical braking and EBD in a BEV. Ji et al. [119] developed a regenerative braking strategy considering accelerator and brake pedal inputs, SOC, and vehicle speed, demonstrating an increase in energy recovery. Wen et al. [120] used an adaptive fuzzy controller for single-pedal regenerative braking, considering stroke change and gradient as inputs. These studies highlight the utilization of fuzzy logic control in early regenerative braking strategies, incorporating multiple inputs to improve energy recapture in electric vehicles.

In their work, Ruan et al. [106] proposed a cooperative algorithm that integrated regenerative braking with driving assistance features like ABS and EBD. The algorithm considered brake signals, regenerative braking limitations, motor torque, gear ratio, and battery charge. It included three blending strategy modes prioritizing energy saving, anti-lock capability, and safety.

A regenerative braking control strategy was proposed by [121] based on nonlinear model predictive control (NMPC) to ensure stability and maximum braking energy recovery. The stability was ensured by distributing braking force on the front wheels with pneumatic brakes and rear wheels with pneumatic and regenerative brakes. The distribution of brake force between pneumatic and regenerative was also optimized to maximize the recovered energy. A longitudinal model with seven degrees of freedom was developed and input variables for NMPC were vehicle speed, front wheel rotation speed, rear wheel rotation speed, desired vehicle speed, and coefficient of the ground.

In [76], a hierarchical braking control was introduced and in its lower-level controller, a frequency-depended braking allocator was applied to distribute braking force into regenerative and friction brakes. The brake pedal travel with linear preset ratios was the input for the regenerative braking control strategy but a braking supervisor was used to switch to friction brake based on the wheels slip ratio and vehicle speed condition. The state of the charge and other characteristics relating to ESS were not considered in this paper. A three-level regenerative control strategy was introduced by [122], taking brake pedal, tire road adhesion, and SOC as input for the highest level. A multi-object optimization method was applied to balance the braking performance, regenerative braking loss efficiency, and battery loss in EVs with a front-wheel-drive system. It was reported that optimization objects presented a clear conflict, and they cannot be optimized at the same time. Another hierarchical regenerative braking control strategy by [71] targeted minimizing the aging of the battery alongside maximizing recovered energy and establishing a secure emergency brake in its up-level controller for a PHEV. A predictive model in this layer took the desired braking force which was calculated using pedal opening and a look table as main input and considering SOC, battery temperature and charging limit, and limitation of braking force in the EM. The control of EM for recovering the energy and pressure controller of the pneumatic brake were presented at the lower level. In [123] a parallel HEV with a two-layer control strategy was studied. The braking force distribution between the front and rear axle was calculated in the first layer regarding braking strength, the fuzzy controller with three inputs of SOC, vehicle speed, and braking strength was presented in the second layer to realize the coordinated control of mechanical braking.

To enhance overall vehicle efficiency, disabling regenerative braking below a low-speed boundary is crucial. Heydari et al. [124] utilized a dynamic detection of the low-speed boundary to shift the EM operating point,

improving energy recapturing capability in EVs. In their subsequent work, they aimed to maximize the recaptured energy through braking by considering the traction motor regenerative braking performance map [125]. Another study by Xu et al. [70] proposed a novel holistic series regenerative brake control strategy for a four-in-wheel motor EV. They optimized the allocation of brake torque based on factors such as SOC, the normal force on the tires, EM rotary velocity, and vehicle longitudinal velocity. Simulation results demonstrated enhanced energy recovery and improved regenerative braking efficiency. These findings contribute to the advancement of regenerative braking technology in electric vehicles.

Zhu et al. [77] introduced a regenerative braking strategy in a front-drive BEV that utilized multi-object optimization of a switched reluctance generator drive system. The aim was to enhance driving range, battery life, and braking comfort. The strategy considered vehicle speed, SOC, and brake pedal input to allocate regenerative and mechanical brakes effectively. A regenerative control strategy for a rear-driven minivan was discussed by [126]. A modified control strategy based on increasing the regenerative braking force on the rear wheels is introduced in this paper to increase recovered energy as the driver pushes the braking pedal. An optimized regenerative brake control strategy algorithm considering brake signal strength, SOC, and EM rotary speed was suggested by [127] to increase regenerated energy and vehicle stability.

## 5) REGENERATIVE BRAKING IN A CONVENTIONAL FCEV

FCEVs have fundamental differences from BEVs. Having a smaller-size battery and the presence of a fuel cell as the main power source need a complex energy management system. Unlike the BEV's battery, the smaller battery size of FCEV limits the amount of storable energy. The presence of FC is also a challenge. FC feeds the traction system mostly and in the event of braking, the battery might be fully charged. In this case, the vehicle is not able to store regenerated energy. Regenerative brake strategy in an FCEV appeared in a limited number of works and the majority of researchers have discussed regenerative braking in FCEVs in the context of energy management systems without further looking into brake control strategy. For instance, in [128], the energy management strategy for a FCEV with a hybrid ESS including battery and UC was studied. The control system considered SOC to select the battery or UC for storing energy of the brake. The system decides to charge UC if the battery is charged. But, the braking strategy and blending of friction and regenerative brake were not included. It seems the crucial link between energy management and regenerative braking needs more study. Discussing details of energy management systems is out of the scope of this article and we keep the focus on the energy recovery strategies implemented in the regenerative braking system.

The regenerative braking of a FCEV with a permanent magnet motor was presented in [129] and a UC was used

to capture braking energy. A fixed ratio was used to allocate the regenerative braking and friction braking with no safety or stability considerations. In [130], a regenerative braking control algorithm was introduced for an FCEV with a brake-by-wire system and regenerative braking on the front wheels. The input was the brake pedal signal, and the use of friction brakes was planned to accrue only when the deceleration demand was higher than a preset value. The negative effect of low speed on the regenerated energy and driving comfort was reduced by defining a weight factor. A fuel-cell hybrid electric bus with rear-wheel-drive was studied in [131]. A coordinated strategy of regenerative braking was applied to distribute force between regenerative braking force and mechanical braking force on the rear and front wheels considering the brake pedal travel. The fuel economy improvement was reported using this strategy compared to a bus without control strategy.

Designing regenerative brake control strategies alongside an energy management system, and evaluating it as a unified system, gives the opportunity to have a broad view of hydrogen consumption, vehicle safety and stability, and regeneration efficiency.

#### 6) DRIVER BEHAVIOR IMPACT ON REGENERATIVE BRAKING

Driving style affects the energy consumption and vehicle range in electric vehicles [132], [133]. In a conventional EV or FCEV, the brake signal from the driver is the most important input for the braking strategy so the driving style also affects recovered energy. A four-year study on EVs showed aggressive driving increases specific energy consumption by 165 percent compared to passive driving [134]. The writers did not specify the rule of regenerative braking in this research. In another research, it was concluded that an aggressive driving style leads to more energy consumption but it results in a 220 percent higher potential for regenerative braking [135]. However, it was reported the increase in energy consumption is higher than the potential harvested energy. It was neglected that the capacity of ESS for storing the recovered energy is limited and the total amount of potential energy cannot be recovered. In [136] the effect of various driving pattern parameters, such as speed and acceleration, on the energy consumption of BEVs was studied. It was concluded that regenerative braking's ability to recover energy decreases the effects of most parameters. Improving driver behaviour effect on the energy efficiency of the EV can be studied on three levels: reports and feedback, driver-aware control strategies, and educating drivers.

Providing Reports and online feedback to the driver is regarded as a helpful approach to improving efficiency [137]. The optimal speed trajectory for an EV was studied in [138] and the authors suggested an eco-driving system to provide online assistance for drivers. A similar system to find the optimized speed profile and communicate with the driver using an interface was proposed in [139]. In [140], it was reported that displaying kinetic energy resources and energy

flow in HEVs could help the driver. The development of autonomous vehicles puts intelligent systems in charge of decision-making and planning and provides excellent opportunities to increase regenerated energy. In [141], it was shown that the energy consumption in an EV could drop by one-third as a result of giving driver feedback. They suggested a mobile application based on the concepts of echo driving to guide drives. The impact of driving style on energy efficiency has encouraged automakers such as Toyota to introduce an echo driving indicator in their products.

In addition to guiding the driver, it is also beneficial to develop driver-aware control strategies. The application of considering driver behaviour in vehicle control was discussed in [142], where a driver model predicts upcoming power demands applied to the energy management of series HEV. It seems that examining driver-aware brake control strategies and energy regeneration requires more attention.

Regarding an educational approach, drivers can be educated about tips and rules to gain higher recovered energy. For instance, in [143], directions for eco-driving are provided. Tips such as "brake gently" with a short description can help drivers adopt driving styles that increase regenerated brake energy. But even in highly motivated drivers for echo driving the difference is substantial and an efficient user-energy interaction is very helpful to guide the driver. The development of autonomous vehicles puts intelligent systems in charge of decision-making and planning and provides excellent opportunities to increase regenerated energy. So, with autonomous driving, there will be control over driving patterns and energy efficiency is likely to increase.

#### 7) REGENERATIVE BRAKING IN AUTONOMOUS VEHICLES

Regenerative braking strategy in vehicles with autonomy level 3 and above which is referred to as autonomous EVs in this paper, will be reviewed in this section. Implementation of GPS and offline road maps alongside a fusion of sensors including radar, lidar, cameras, and ultrasonic sensors for real-time environment perceptions provide data beyond what a human driver can achieve. Furthermore, connectivity in vehicles such as vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) that results in connected and automated vehicles extend the potential of automated driving [144].

Since in autonomous vehicles, there is control over both acceleration and deceleration, the output of speed planning replaces the driver's brake pedal signal. The other type of using smart regenerative braking is by automating only the brake in the car-following scenarios which will be covered in this paper. The focus in autonomous vehicle studies has been on energy-efficient driving strategies and eco-driving strategies to reach the optimal speed and acceleration to decrease energy consumption. In [36], it is shown that to travel between two stop points the most efficient way is to accelerate with maximum power and then coast with no brake to stop. However, coasting is not possible or safe in all situations [35], especially in urban areas. Based on our

review many researchers have overlooked the capability of regenerative braking to recover energy in intelligent EVs or FCEVs and its potential and limits are neglected.

Regenerative braking limitations, such as the maximum regenerative braking capability and the inability to harvest mechanical energy at very low speeds, were discussed in a study on eco-driving by Mohammadi et al. [145]. A car following a control strategy for an intelligent BEV was proposed by [146] including a regenerative braking strategy to increase energy efficiency and safety. The proposed adaptive cruise control framework had two levels and the brake intensity was calculated based on the desired acceleration which was the output of a higher level. In the lower-level controller, by considering the available regenerative power and adhesion coefficient, a braking strategy was developed.

In [147], a car-following scenario was proposed with manual acceleration and a smart regenerative system for BEV. The applied deceleration planning in this research takes the accelerator pedal position, brake pedal position, acceleration, velocity, relative distance, and relative velocity as inputs to calculate a reference deceleration. This acceleration command results in the torque output of an acceleration controller and a feedback-and-feedforward controller. In [148], a front-wheel drive BEV with an ultracapacitor as an auxiliary power source was the subject of a study for optimal speed planning. The brake force is distributed between the rear and front wheel and a fuzzy controller with three inputs of SOC of UC, brake intensity, and vehicle speed, generates the regenerative brake force coefficient like a conventional vehicle. Since it is a connected and automated vehicle, signal light status, and timing information from infrastructure are considered constraints for optimization speed trajectory at the signalized intersection.

In [149], a smart regenerative brake was developed for autonomous vehicles to take control of deceleration situations without the driver's intervention. After determining the driving state, a reinforcement learning algorithm manages the output desired acceleration by considering two deceleration planning. The driving data used for this approach were driver acceleration and brake pedal input, vehicle speed and acceleration, preceding vehicle speed, relative distance, EM torque, and EM speed.

In [150], the limitation of low-speed regenerative braking, maximum braking force available on the axle with regenerative braking, and maximum charging current was considered for optimized speed planning for an autonomous and connected EV in a signalized roadway with intersections.

In [151], a speed planning algorithm for the rule of driving assistance system or part of autonomous vehicle control was proposed. It was assumed that the intersection traffic data is collected by V2I and an optimized speed planning algorithm, based on information was applied to increase energy recovery and drive comfort. A genetic-based eco-driving technique was studied by [152], putting regenerative braking into account. In [69], an optimal deceleration planning system was presented for connected and automated

electrified vehicles facing an upcoming deceleration event. The inputs of deceleration planning were initial speed, final speed, residual distance, and required time. The objective of the optimal control problem was to maximize regenerative braking energy apprising the regenerative power limit of EM. For the deceleration, vehicle dynamics and forces were taken into account.

When a driver is in charge of controlling a vehicle, acceleration commands are the inputs of the regenerative braking strategy. The driver can be guided to use pedals more efficiently, but it is still a challenge to obtain the best inputs. In the autonomous vehicle, there is a chance to look one step back and calculate the best acceleration or deceleration commands. Then, the optimized speed would be the input for the braking strategy to guarantee the vehicle's safety and stability. This shows the great potential to increase energy efficiency in autonomous vehicles.

Connected and automated fuel cell hybrid electric vehicles (CAFHEVs) represent the next generation of FC-based road transport. Recent studies have focused on co-optimization by merging speed planning and EMS to enhance the performance of these vehicles. This method involves calculating the optimal speed at the upper level and optimizing the EMS based on the calculated speed. In a study by Jinqian et al [153] a co-optimization fuel cell bus with regenerative braking was studied to reduce hydrogen consumption. The upper level used dynamic programming for speed planning on the road with intersections and the lower level used MPC for the EMS. The computation time and load in the co-optimization problems is an important factor and in [154] a bi-level convex co-optimization method for a CAFHEV was suggested in this regard. Authors reported improved computational time, but the effect of regenerative brake was not discussed. In [155] another method to reduce the complexity of co-optimization was introduced and in the speed planning layer, the limits of EM to regenerate energy on a sloped road were taken into account. Authors in [156] proposed a co-optimization for the intelligent FCHEV. The work was continued in [157] by considering regenerative brake and the urban traffic setting, followed by another study [158] with considering dynamic road curve. In [159] and [160] the studies for the co-optimization did not include the effect of regenerative braking on the upper layer speed planner.

Despite the differences between FCEVs and other types of EVs, research on autonomous FCHEVs is very limited. In addition, using perception and online detection approaches while considering regenerative braking applications has emerged in a limited number of studies.

### C. REGULATIONS AND STANDARDS ON REGENERATIVE BRAKING

It is important to note commercial application regenerative braking systems must undergo rigorous tests and meet safety and stability standards. These regulations and standards aim

to ensure the proper functioning, efficiency, and safety of regenerative braking technology (as a part of the vehicle braking system), including aspects like energy recovery, braking performance, electromagnetic compatibility, system integration, and adherence to environmental and safety regulations. While covering all the regulations on braking in a study is not feasible, the safety measures could be vital as they may directly affect the regenerated energy.

The majority of studies have limited their study to the energy efficiency aspect of regenerative braking without considering regulations and related standards, while some studies have ensured that the braking strategy complies with regulations. There are several standards available related to braking such as FMVSS 135, ECE R13, and ISO 6469. ECE R13, also known as Regulation No. 13 of the United Nations Economic Commission for Europe (UNECE), is a worldwide accepted standard that specifies uniform provisions concerning the braking system of motor vehicles. This regulation is acknowledged as a valid braking standard under the 1958 agreement and is adhered to by all United Nations (UN) members, including Australia, Austria, Japan, Germany, Italy, Switzerland, Norway, the Russian Federation, the United Kingdom (UK), and the United States of America (USA) [118].

Among reviewed references, all the works that considered compatibility with a standard considered, have used ECE R13 [106], [113], [117], [118], [122] [77], [123] [126], [127] [146]. The Chinese GB/T B594-2033 regulation was used by one reference [131].

#### IV. ENERGY HARVESTING FROM SUSPENSION SYSTEMS

When a vehicle moves on a road there is a chance to harvest vertical vibrations caused by uneven roads and convert them into electrical energy. Traditionally shock absorbers in parallel with suspension springs are applied to decrease vibration by dissipating that energy as heat but a regenerative suspension system (RSS) provides a prospect to harvest vertical vibrations [161], [162]. Fig.12 shows the general idea of an RSS. When a vehicle crosses the road, there is linear movement in the suspension system. This movement is used to produce electricity in a direct or indirect approach. Finally, the electricity is stored in an ESS. A typical mid-sized passenger car there is the potential to harvest energy ranging from 100 W to 400 W on a good road with approximately 96 Km/h [161]. This harvesting approach has been studied by many researchers before, both on conventional and electric vehicles, but it was reported to be more effective in HEVs and EVs [163]. The fuel improvement for a conventional passenger car with regenerative suspension was reported to be between 2 to 3 percent while numbers for the EVs vary between 7 to 10 percent. The suspension system of an EV and a conventional vehicle could be the same (despite some topologies such as in-wheel-motor). Still, it should be noted that EVs have a proper ESS to store any regenerated energy, but when it comes to conventional vehicles the storage and use of it should be considered.

The harvested energy in a conventional vehicle should come alongside an auxiliary ESS or the energy must be directed to feed auxiliary devices. In this paper, we did not limit the review on RSS to works that have expressed EVs as the main target of their study.

It should be noted that potential harvestable power in literature has been reported in a very wide range and these results may suffer from using a simple quarter-car model, using tire-road point contact model, and testing on the simulated road that is too rough in comparison with the real roads [164]. The dissipated instant power by a passive suspension system can be calculated according to [165]:

$$P_i(t) = F_d (\dot{Z}_s(t) - \dot{Z}_u(t)) = C (\dot{Z}_s(t) - \dot{Z}_u(t))^2 \quad (8)$$

The instant power denoted as  $P_i$  is determined by the multiplication of the damping force  $F_d$  and the suspension velocity denoted as  $\dot{Z}_s(t) - \dot{Z}_u(t)$ .  $C$  represents the damping coefficient.

The equation gives a basic idea of dissipated energy, however, the regenerated energy depends on the implemented method. The regenerated energy in the suspension system depends on four basic factors depending on the vehicle or the road [166]:

##### A. THE CONDITION OF THE ROAD AND ITS ROUGHNESS

the oscillation created on a very plane surface does not create considerable vibration, hence bumpy roadways are more suitable for the regenerative suspension system (RSS). In [167], an energy recovery system for a mild HEV including regenerative suspension was studied. A linear motor was used to harvest vibration. The harvested energy on the C-class road was considerably higher than on A-class roads.

##### B. VEHICLE MOVING SPEED

In [168], it was shown that a higher traveling speed of a vehicle results in higher harvested energy.

##### C. DAMPING AND STIFFNESS OF THE TIRE AND SUSPENSION

The power in the vehicles' suspension depends on tire stiffness, the higher stiffness in the wheel results in higher regenerative power. On the other hand, ride comfort is affected by suspension stiffness [161].

##### D. THE LOAD OF THE VEHICLE

In heavier vehicles such as trucks and buses, there is higher vibration intensity.

The suspension of a vehicle can be classified as passive, semi-active, and active. Because of reliability and the simple structure, most vehicles are equipped with passive suspension [169]. In the passive suspension, the harvested energy will be stored to be used based on vehicle demand. Since semi-active and active suspension uses power to deliver more riding comfort, the harvested energy can be used as a means to reduce their energy demand.

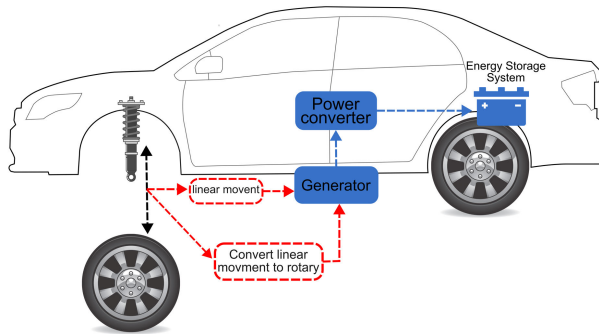


FIGURE 13. The scheme of RSS.

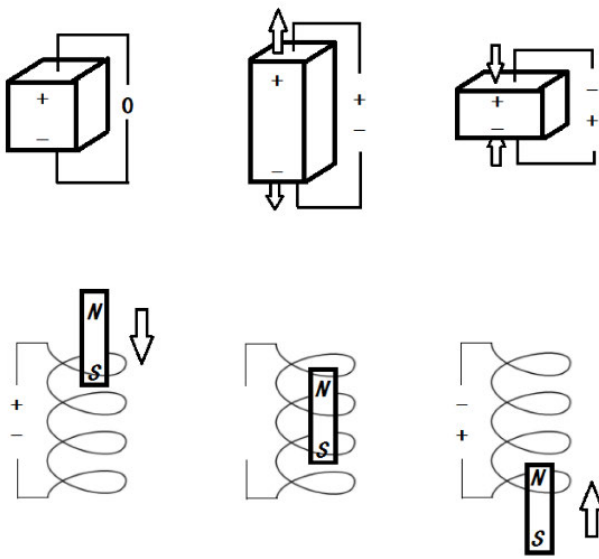


FIGURE 14. Piezoelectric (up) and electromagnetic (down) regeneration [170].

### E. ENERGY HARVESTING IN PASSIVE SUSPENSION SYSTEMS

There are three approaches to harvesting mechanical energy and vibration: a piezoelectric transducer, an electromagnetic transducer, and an electrostatic transducer. The first two methods have been applied and tested in numerous studies. Fig. 14 shows the basic scheme of piezoelectric and electromagnetic regeneration.

In general, piezoelectric offers power density, compact size, and ease of use, but electromagnetic transducers outperform them in terms of a lower strain, low resonant frequency, and higher displacement. The last factor is very important since there is a maximum displacement of 10 cm in passenger vehicles. Regarding these differences, electromagnetic-based RSS has attracted more studies [166].

The electromagnetic regenerative suspension includes direct (linear) and indirect (rotary) types. In a direct setup, the shock absorber's cylinder contains permanent magnets and coils. It produces electricity when a relative linear movement between coils and magnets happens. The basic design suffers from limited damping and limited power density, and studies

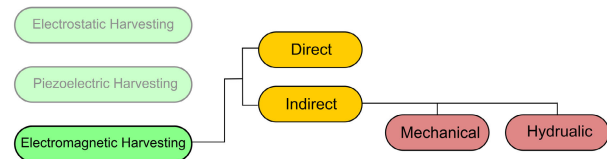


FIGURE 15. Classification of electromagnetic-based harvesting.

have suggested the use of parallel hydraulic damper and considering new designs to address these shortcomings [171]. The indirect type needs a mechanical or hydraulic mechanism to convert the linear motion to a unidirectional rotary motion with desirable velocity and then uses a DC generator to produce electricity. Mechanical mechanisms such as rack and pinion, ball screws, and algebraic screws have been mentioned in the literature. The indirect type suffers from energy loss due to friction in the complicated mechanism [172]. Fig. 15 shows the classification of electromagnetic-based suspension systems.

In [173], a half-scale prototype of a direct actuator generated 16-64 W of power. Another study [174] introduced a direct electromagnetic energy harvester with four configurations, achieving 2.8 W at 0.11 m/s. For range-extended EVs, [175] proposed an indirect mechanical RSS with dual-overrunning clutches, yielding 44.24 percent efficiency and 4.302 W power output. [176] presented a non-contact piezo-magneto harvester, with regenerative power ranging from 16 W to 242 W at 120 km/h. In [177], a twin ball screw mechanism achieved 36.4 percent efficiency and 3.701 W output power at 1 Hz frequency and 3 mm amplitude. To address issues with traditional mechanisms, [178] proposed an algebraic screw linkage mechanism. [179] studied a double-sided arm-toothed indirect RSS for semi-trailer trucks, obtaining power levels of 0.33 W, 1.33 W, 5.24 W, and 21.3 W for road classes A, B, C, and D respectively. In [180], a linear electromagnetic generator-based RSS provided continuous power regardless of position or speed, with 39.46 percent efficiency at 2.5 Hz and 7 mm amplitude. Additionally, [181] proposed a mechanical electromagnetic harvester using helical gears and dual tapered roller clutches, achieving 40 percent efficiency and 270 W power output at 2.5 Hz and 5 mm amplitude.

An autonomous new energy bus was the subject of a study to regenerate energy from vibration on the road [182]. The autonomous bus could benefit from 17 W regenerated power which was enough to feed a LIDAR for 323 days. EVs with in-wheel motors have larger unsprung mass in their suspension and this results in more discomfort and safety on uneven roads [183]. In [184] writers in the search for a regenerative suspension suitable for the setups of in-wheel electric vehicles investigated a suspension system embedded with an electromagnetic-tuned mass damper (TMD). The results of the simulation on the 11 DOF model of the vehicle indicated a maximum RMS power of 58 W at 30 m/s and on a D-class road.

The design method of the hydro-magneto-electric regenerative shock absorber was reported in [185] to increase ride comfort in parallel with harvesting energy. The design included a hydraulic cylinder-tube system, gear system, hydraulic motor, and electric generator. The measured power output of the prototype was between 7 W to 14 W (with an input frequency of 1 and 1.5 respectively), smaller than the maximum of 18 W in the simulation. A hydraulic integrated interconnected regenerative suspension was studied in [186]. It was shown with a half-car model that an off-road vehicle on a C-class road at the speed of 72 K/h can harvest the power of 417.40 W. A compact design of an electro-hydraulic system was suggested in [187]. The highest regenerative power of 75 W was obtained in the hard-driving tests compared to 5 W in normal-driving tests. Bench test results for another electro-hydraulic interconnected RSS indicated a potential of harvest 525 W at the speed of 8 Km/h on a D-class road for an SUV [188]. To increase the safety of the vehicle an electromagnetic harvester co-existing with a conventional passive shock absorber was introduced [189]. The test results of the prototype showed power output ranging from 0.64 W to 1.08 W at the frequency of 10 Hz and amplitude of 2 mm.

To increase the safety of the vehicle an electromagnetic harvester co-existing with a conventional passive shock absorber was introduced [189]. The test results of the prototype showed power output ranging from 0.64 W to 1.08 W at the frequency of 10 Hz and amplitude of 2 mm.

A piezoelectric energy harvester for an electric truck was designed [191] and the RMS of harvested power was reported to be 18.83 W. The maximum of 102.24 W was obtained on a pulse road drive at the speed of 30 km/h. A mathematical model for dual mass piezoelectric bar harvest was developed by [192], and for specific material and geometry parameters, the possibility of harvesting 738 W was announced. Simulation outcome of another piezo harvester in parallel with the conventional suspension system calculated 322.4 W of regenerative power [193].

#### F. ENERGY HARVESTING IN SEMI-ACTIVE AND ACTIVE SUSPENSION SYSTEMS

Active suspension needs considerable energy to run which is a barrier to widespread use of it [161] and regenerative active suspension provides the opportunity to act as a partly self-powered damper that offers better ridding and road handling [165]. The idea of using regenerative active suspension in HEV was investigated [194], and based on the simulation results the fuel economy will improve with this method. Fig. 16 illustrates a basic quarter model of an active suspension system with a regenerative force actuator. The  $Z_s$  and  $Z_u$  are the vertical displacements of the sprung mass and un-sprung mass respectively, and  $Z_r$  is road excitation.  $m_s$  represents the varying sprung mass, and  $m_u$  refers to the un-sprung mass.  $k_t$  is the tire damping coefficient and  $c_t$  stands for the damping coefficient of the tire. The actuator force is represented with  $U$ . The equations of vertical motion can be

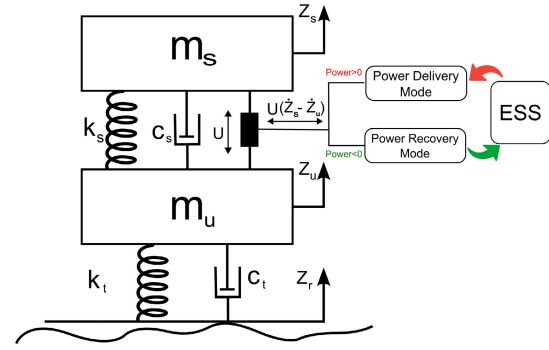


FIGURE 16. 2-DOF quarter model of the regenerative active suspension system.

described as follows [195]:

$$m_s(t)\ddot{Z}_s(t) = k_s (Z_s(t) - Z_u(t)) - C_s (\dot{Z}_s(t) - \dot{Z}_u(t)) + U(t) \quad (9)$$

$$m_u(t)\ddot{Z}_u(t) = k_s (Z_s(t) - Z_u(t)) + C_s (\dot{Z}_s(t) - \dot{Z}_u(t)) - k_t \times (Z_u(t) - Z_r(t)) - C_t (\dot{Z}_u(t) - \dot{Z}_r(t)) + U(t) \quad (10)$$

And the active suspension power,  $P_{AS}$ , is calculated as:

$$P_{AS} = U(\dot{Z}_s - \dot{Z}_u) \quad (11)$$

When the system is working in the power recovery mode the power is negative and the regenerated energy could be delivered to ESS. In [196], a semi-active regenerative suspension with an adjustable shock absorber and a linear motor was introduced. The system contained a UC to store generated energy and the motor was capable of controlled damping resulting in 15 percent improved riding comfort. A series of tests on an electro-hydraulic semi-active damper prototype for off-road vehicles [197] resulted in an average of 110.6 W regenerative power.

In [190], a regenerative active suspension applied on an in-wheel motor-driven BEV was introduced with dual actuators to increase comfort. Based on the road type used for the test, the regenerated energy ranged between 4.9 W to 45 W. An ESS including an onboard low-voltage battery pack and a UC was proposed to increase the harvesting efficiency. Another study of in-wheel EVs was in [183] and an unmanned ground vehicle (UGV) with active electromagnetic suspension was proposed. Based on the simulation the system was able to regenerate 10 W on a B-class road at high speed. Table 4 reports the references that have considered applying the suggested RSS in an EV.

Regarding the harvestable output power, it will be the same for any type of vehicle with the same weight and RSS and from the same class, so it seems not necessary to conduct different research for FCEVs. That might be the reason for the lack of studies (to the best of our knowledge) on RSS in FCEVs. The only notable point to consider is the weight of FCEVs, which tends to be slightly higher compared to same-class HEVs and BEVs. For example, the

**TABLE 4.** References that have considered the application of proposed RSS in an EV.

| No. | References | Vehicle type       | Energy Harvesting Technology     | Road Disturbance             | Regenerated Power (Total) |
|-----|------------|--------------------|----------------------------------|------------------------------|---------------------------|
| 1   | [183]      | In-wheel Motor BEV | Active Direct Electromagnetic    | Road Class B                 | 10 W                      |
| 2   | [190]      | In-wheel Motor BEV | Active Indirect Electromagnetic  | Road Class C                 | 4*(49.2) W                |
| 3   | [182]      | Electric Bus       | Passive Indirect Electromagnetic | 2.5 Hz with 7 mm Amplitude   | 4*(4.25) W                |
| 4   | [184]      | In-wheel Motor BEV | Passive Direct Electromagnetic   | Road Class D                 | 58 W                      |
| 5   | [181]      | Not Specified      | Passive Indirect Electromagnetic | 2.5 HZ with 5 mm Amplitude   | 270 W                     |
| 6   | [175]      | PHEV               | Passive Indirect Electromagnetic | 2.5 Hz with 7.5 mm Amplitude | 4*(4.302) W               |
| 7   | [177]      | PHEV               | Passive Indirect Electromagnetic | 1 Hz with 3 mm Amplitude     | 4*(3.701) W               |
| 8   | [176]      | Not Specified      | Piezoelectric Energy Harvester   | Road Class E                 | 242 W                     |

Toyota Mirai is approximately 300 kg heavier than the Tesla Model 3. As discussed, heavier weight can contribute to a higher amount of harvested energy. In addition, there was no research including a field test of RSS in FCEV in the literature.

## V. OTHER SOURCES FOR ENERGY HARVESTING

There are other minor opportunities to harvest energy in a BEV or FCEV, and recovered energy can be stored or used for running sensors and electrical devices. In this section, we will review these methods that have not been widely studied. Some of the works are not proposed exclusively for EVs and are applicable in any type of vehicle, but because an EV always comes with an ESS, it is simpler to apply these works to an EV. Considering the nature of these methods, which are independent of the drivetrain and do not exert additional pressure on the energy storage system (ESS), their application to FCEVs and EVs is generally similar in most cases.

### A. HARVESTING HEAT AND BODY VIBRATION

HEVs have ICs to run alongside an EM and in the IC engine there is considerable energy loss. Recovering heat energy in IC engine have been studied and reviewed in many works [52], [198], [199], [200], and the nature of the current paper is not circling around HEVs, so this part is not covered in the present paper. Regarding other heat sources in [201], recovering heat from brake disks using a thermoelectric generator was proposed, and based on the simulation results, 4 W of harvested energy is available at a minimum.

Other than regenerating energy in the suspension system the opportunities to harvest energy from general body vibration or the energy during steering have been studied in the literature. In [202], the design of a piezoelectric harvester to recapture energy from an autonomous vehicle's vibration was presented and tested. A hybrid kinetic energy harvester (KEH) for an autonomous bus was presented in [203]. The KEH harvests inertial kinetic energy during accelerating and turning in the vehicle using a small generator and piezoelectric beam in an uneven table and base (Fig.17).

The highest power out of the KEH was 8.31 mW at 8 m/s<sup>2</sup> acceleration and it is capable of powering 54 LED lights.

### B. ENERGY HARVESTING FROM WHEELS AND TIRES

In driving a vehicle, the rolling speed of the tire changes, and the tires are under load. Considering this situation there is a harvesting potential by implementing triboelectric and piezoelectric harvesters [204]. The harvested energy from the tires can be used to power pressure and speed sensors on the wheel [205] offering no need for battery replacement and longer durability.

In [206], it was estimated that more than 1 kW of energy wastes as the pneumatic tire in a passenger car deflects and the authors presented a piezoelectric harvester, capable of recovering 42 mW. Another piezoelectric harvester was studied in [207] to act as a power source for strain sensing and wireless data transfer. The recovered energy was sufficient to feed 78 LED lights. A rainbow-shape piezoelectric material layer for mounting on the internal side of a pneumatic tire was proposed in [208] and simulation data indicated 5.85 mW harvesting power is achievable.

To monitor the pressure of a tire, a triboelectric nanogenerator was proposed in [209]. The harvested power of 22.3 mW was reported at the speed of 100 rpm. A hexagonal-shaped triboelectric harvester was suggested in [210] to power a wireless tire pressure sensor (Fig.18). It was reported that applying 500 units of this harvester to a standard tire at the speed of 100 km/h would result in 1.2 W recovered power.

In some references, the implementation of energy harvesters on the wheel (rim-mounted harvesters) has been presented. In [211], a piezoelectric harvester with the application of stochastic resonance was attached to the wheel. The mechanism included piezoelectric film and a magnet shown in Fig.19. Another wheel-attached piezo harvester was proposed in [212] for an intelligent vehicle wheel system with sensors inside such as temperature, pressure, deformation, and torque sensors. The design was capable of harvesting between 0.61 to 6.28 mW at speeds of 40 to 120 km/h. A weighted pendulum was studied in [213] to recapture energy from a rotating wheel with the pick converted power

## Electric Driverless Bus

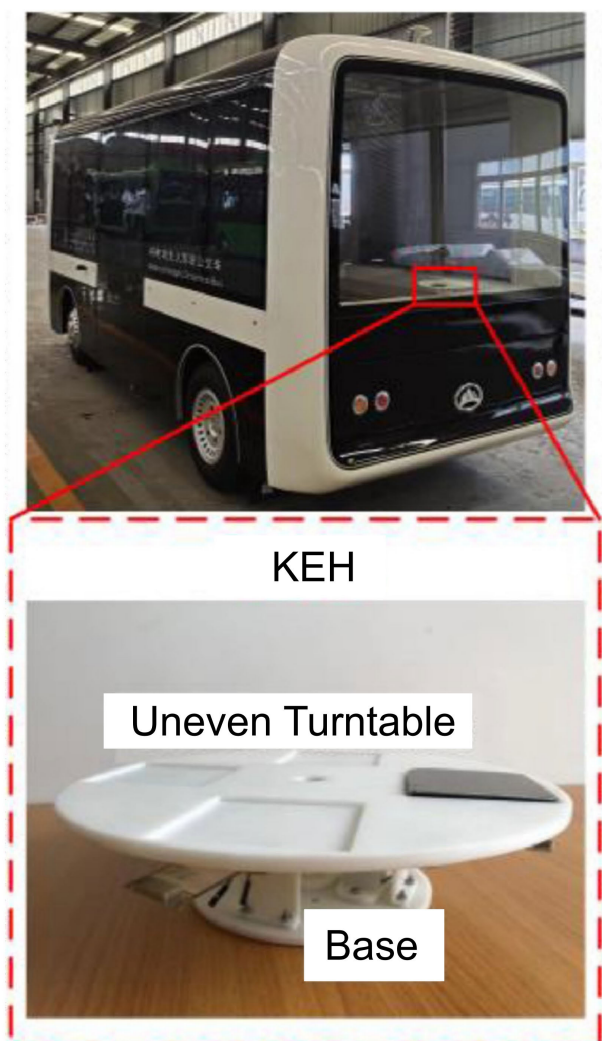


FIGURE 17. KEH energy harvester [202].

of 0.9-2.6 mW. The authors reported approximately 0.2 to 0.3 mW of harvested energy from the physical model in [214].

### C. WIND ENERGY HARVESTING

As was shown before, based on the drive cycle between 30 to 47 percent of the energy directed to the wheels is lost due to wind resistance. One solution to this problem is to optimize the aerodynamic design of the vehicle, which has been studied comprehensively before and is beyond the frames of this paper. In some references, the application of a vehicle-mounted wind turbine (VMWT) has been investigated [215], [216], [217], but since the VMWT has weight and increases the drag force, it reduces vehicle efficiency. So, reporting the power produced by VMWT without considering the drop in vehicle efficiency is misleading, and it might be the case in [34].

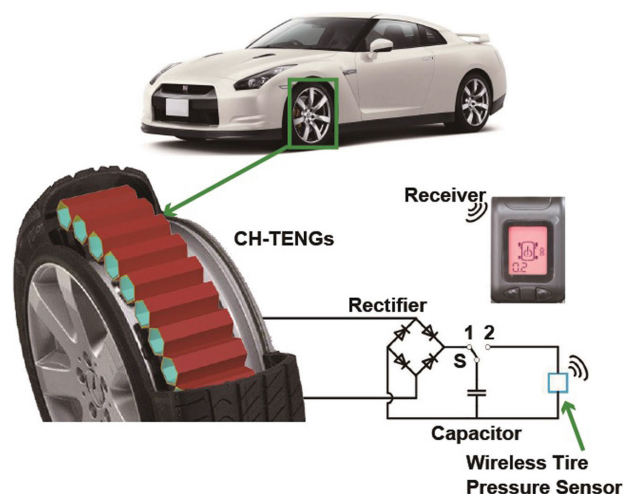


FIGURE 18. Energy harvesting from the tire [210].

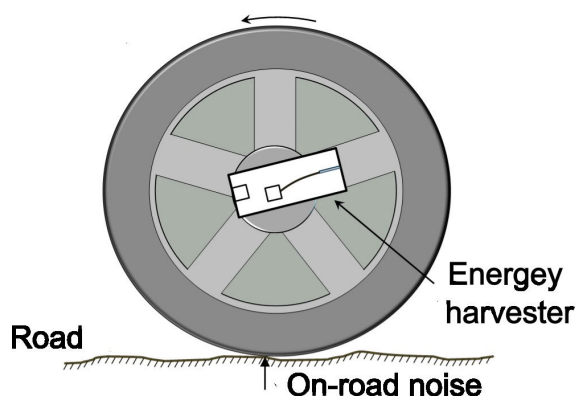


FIGURE 19. Rim-mounted energy harvester [211].

In [218], a flutter piezo-electromagnetic hybrid harvesting structure was proposed to recover wind and vibration during vehicle movement. Its structure included a piezoelectric beam with a tip magnet, a rigid airfoil, and an electromagnetic harvester fixed in front of the airfoil. The experimental result showed the harvested power of 14.5 mW in the piezo harvester and 31.8 mW in the electromagnetic harvester at the wind speed of 18 m/s.

### D. SOLAR ENERGY HARVESTING

Harvesting solar energy and converting it into electricity for different applications has been studied for many years and with the current market trend in the price of photovoltaic (PV) modules, solar-powered EVs (PVHEV) is getting more serious attention [219]. However, with the current efficiency of available PV panels, even at midday with the highest sunlight profile, the PVHEV with the 8 m<sup>2</sup> PV panel can generate a maximum of 11 horsepower [220]. Hence, considering EVs with commonly over 100 kW traction EMs, a full solar electric vehicle is not practical, but Hybrid solar vehicles are beneficial [221]. The roof of the vehicle as the

main space to apply solar panel needs should be designed with proper geometry and a moving solar roof increases harvested solar power in most cases [222]. Non-uniformity of solar irradiation and changes in temperature also affect PV efficiency and are a challenge for this type of HEV [223].

The contribution of applying solar panels to increase the travel distance of EVs was discussed in [224] and a significant increase in the driving range on urban roads was reported. An off-road solar-powered electric vehicle was designed in [225]. The increase in vehicle range and lower carbon footprint were reported as pros of the design. A battery/PV/wind hybrid power vehicle with a 19.2 kWh Li-ion battery was proposed in [226] and authors reported a 19.6 km extended range for a PHEV. The application of solar harvesting alongside regenerative braking in a through-the-road HEV was studied in [227]. Hybrid vehicles have the capability to utilize a combination of fuel cells, batteries, and solar panels as simultaneous energy sources. The modeling and simulation of HEV in MATLAB Simulink with FC, battery, and solar panels were presented in [228]. A hybrid vehicle with an integrated energy system including fuel cells and PV was studied in [229]. The proposed HEV was compared with an FCHEV without the solar panel and the use of PV resulted in less fuel cell destruction. In [230] a Zero-Fuel-Zero-Emission (ZFZE) electric vehicle with FC, PV panels, and wind turbine was introduced. Based on the simulation the authors reported a travel distance of 260km in 4.7 hours. However, the study did not include the analysis of optimal energy management.

Overall, PVHEVs are in the developing phase with clear advantages, and with future development and progress, they might gain more market share as the PV panel gets cheaper and their efficiency is increased. Utilizing advanced look-ahead techniques is required to tune the energy management and control for maximizing the harvested energy from the panels [231]. Solar charging stations are another solution to power electric vehicles with clean energy that shifts the harvesting unit from the vehicle to the infrastructure [232].

### E. RADIO FREQUENCY ENERGY HARVESTING

Electromagnetic waves offer diverse opportunities for energy harvesting, including visible light, ultraviolet rays, and more. One notable application is the conversion of radio waves into direct current (DC) power. A prime example of this is radio frequency identification (RFID) tags, which exemplify a straightforward utilization of this technology [233]. There are two approaches to RF energy harvesting. First, it can be obtained from dedicated sources that are intended for this specific application. The roadside charging units can be connected to the existing power grid, allowing them to draw electricity from conventional sources. Alternatively, they can be integrated with renewable energy systems, such as solar panels, enabling the use of clean and sustainable energy. This versatility makes roadside charging units a practical solution for providing electric vehicle charging infrastructure

in remote and environmentally conscious areas. Exploring the subject of wireless charging falls outside the scope of this paper but can be further investigated, particularly within the area of wireless charging technologies. In the second approach, the focus is on harvesting ambient RF signals for energy harvesting. These signals, which include transmissions from TV and radio towers, are primarily intended for other applications. However, they can still serve as valuable sources of energy that can be harvested and utilized for various purposes [234], [235]. The ambient RF energy harvesting is promising, particularly in urban areas characterized by a high density of radio waves.

RF energy harvesting has the potential to supply energy for low-power applications in EVs as well as other forms of transportation, such as unmanned aerial vehicles (UAVs). However, ambient sources have some disadvantages, for instance, low energy density [236]. RF energy harvesting has been a subject of investigation in numerous studies, including research on simultaneous wireless information and power transfer (SWIPT) [237], [238], [239]. However, its specific application for electric and autonomous vehicles has not been extensively studied and comprehensively explored.

### VI. FUTURE TRENDS AND RESEARCH GAPS

Research on energy harvesting and recovery methods presents a valuable opportunity for automakers to improve the energy efficiency of vehicles available on the market. By exploring and implementing these innovative methods, automakers have the potential to revolutionize the way vehicles utilize and conserve energy. In fact, several energy harvesting and recovery methods have already found their way into vehicles that are currently available in the market. These methods are highlighted in Table 5, which provides a comparative analysis of different vehicle models and their energy recovery capabilities. One notable example of such technology is regenerative braking, which has been successfully integrated into EVs for a long time. While regenerative braking has become a standard feature in many EVs, it is important to note that information regarding the maximum regenerative braking capacity is not always readily available for every product on the market. As mentioned earlier, it is important to consider that energy recovery is influenced by a multitude of factors. Consequently, the energy numbers presented in Table 5 may vary across different situations and conditions.

In the previous sections, this paper reviewed energy loss in a vehicle, the architecture of FEVs, energy harvesting potentials in BEVs and FCEVs from different sources, and various opportunities to recover energy in conventional or autonomous vehicles. Based on this analysis multiple suggestions and challenges are presented in the following.

#### A. REGENERATIVE BRAKING IN AUTONOMOUS ELECTRIC VEHICLES

Many references have worked on the increased energy recovery as the driver pushes the brake pedal but when it

**TABLE 5. Examples of energy recovery and harvesting in commercial EVs.**

| Method               | Vehicle Type | Brand and Model        | Recovered or Harvested Energy or Its Equivalent | Reference |
|----------------------|--------------|------------------------|-------------------------------------------------|-----------|
| Solar Harvesting     | HEV          | Hyundai Sonata Hybrid  | The annual range can be increased up to 1300 km | [240]     |
|                      | BEV          | Aptera                 | 700 W of continuous charging power              | [241]     |
|                      | HEV          | Karma GS-6             | 200 W of power from roof panel                  | [242]     |
| Regenerative Braking | BEV          | Audi e-tron            | a maximum of 220 kW at a speed of 100 km/h      | [243]     |
|                      | BEV          | Porsche Taycan         | up to 275 kW                                    | [244]     |
|                      | BEV          | Tesla (3, Y, S)        | N/A                                             | [245]     |
|                      | HEV          | Toyota Prius           | N/A                                             | [246]     |
|                      | BEV          | Volkswagen Id.Buzz pro | up to 100 kW                                    | [247]     |
|                      | BEV          | KIA EV6 GT             | Peaks at over 300 kW recuperation               | [248]     |

**TABLE 6. Recent publications on co-optimization in FCEVs.**

| Reference | Publishing year | Methods used in co-optimization | Driving scenario                                   | Test                             |
|-----------|-----------------|---------------------------------|----------------------------------------------------|----------------------------------|
| [153]     | 2021            | DP + MPC                        | Two intersections, with and without other vehicles | Hardware in the loop (VTSsystem) |
| [154]     | 2022            | MOSEK solver + ADMM algorithm   | Signalized intersections                           | MATLAB                           |
| [156]     | 2022            | Gradient-based MPC + MPC        | Sloped road with other vehicles                    | MATLAB                           |
| [159]     | 2022            | MPC                             | Simulated traffic situation                        | VISSIM                           |
| [160]     | 2022            | Constraint stochastic MPC       | Simulated traffic situation                        | VISSIM                           |
| [157]     | 2022            | Gradient-based MPC + MPC        | Sloped road with a traffic light and speed limit   | MATLAB                           |
| [155]     | 2022            | DP + PNP                        | Sloped road                                        | MATLAB                           |
| [158]     | 2023            | Gradient-based MPC + PRA-ECMS   | Road with dynamic curve                            | MATLAB                           |

comes to autonomous vehicles the focus is on optimized speed planning without considering regenerative braking. The potential of regenerative braking during autonomous navigation has been overlooked in most cases by researchers. In addition, in real-world situations, the driving process gets interrupted by different unpredicted events such as pedestrians or other vehicles' maneuvers, and considering only stop signs and traffic lights for regenerative braking is not enough. The information from LIDAR, cameras, radar, and other sensors can be utilized not only to conduct safe braking but also to optimize the recovered energy through regenerative braking. Based on echo-driving principles, it is better to limit braking situations, but relying only on coasting is not safe and practical. Using look-ahead technologies and long-term road anticipation can

be employed to improve energy efficiency in an EV in braking events.

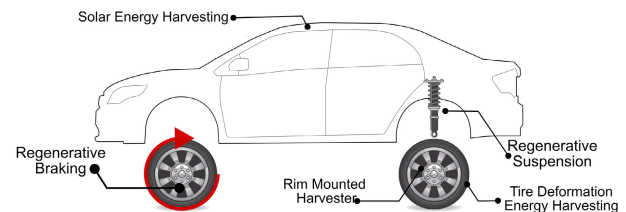
## B. REGENERATIVE BRAKING IN FUEL CELL ELECTRIC VEHICLES

Based on our current knowledge, there is a limited number of studies available on regenerative braking in fuel cell electric vehicles (FCEVs), particularly in the context of autonomous FCEVs. One area of focus that scholars have been exploring is co-optimization. Table 6 provides a compilation of recent studies conducted on this topic and Highlights co-optimization in CAFHEVs as the emerging trend. However, the mentioned studies in Table 6 do not investigate the potential of switching between battery and FC before braking in terms of increasing recovered

**TABLE 7. Effects of vehicle and environment parameters on main Energy harvesting and energy recovery methods.**

| Method                         | Vehicles Factors                                                                                                                                                                                                                                               | Environment                                                                                                                                                                        |
|--------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Regenerative Brake             | <ul style="list-style-type: none"> <li>Higher speeds and weight result in higher harvestable energy</li> <li>EM capacity to regenerate electricity bounds the regenerated power</li> <li>The ESS type greatly impacts storing the recovered energy.</li> </ul> | <ul style="list-style-type: none"> <li>Urban traffic is more suitable</li> <li>Aggressive driving results in more regenerated energy</li> </ul>                                    |
| Regenerative Suspension        | <ul style="list-style-type: none"> <li>Higher traveling speed of the vehicle results in higher harvested energy</li> <li>In heavier vehicles such as trucks regenerative suspension energy is higher</li> </ul>                                                | <ul style="list-style-type: none"> <li>Bumpy roadways are more suitable for regenerative suspension systems</li> </ul>                                                             |
| Solar Harvesting               | <ul style="list-style-type: none"> <li>With a more overall dimension of the vehicle and subsequently solar panels, energy harvesting increases.</li> </ul>                                                                                                     | <ul style="list-style-type: none"> <li>Depends on the available sunlight</li> </ul>                                                                                                |
| RF Harvesting                  | <ul style="list-style-type: none"> <li>Speed and direction of the vehicle can effect signal strength</li> </ul>                                                                                                                                                | <ul style="list-style-type: none"> <li>Ambient FR harvesting is more suitable for urban areas</li> <li>In rural areas, the distance from dedicated sources is important</li> </ul> |
| Rim and Tire Energy Harvesting | <ul style="list-style-type: none"> <li>Based on the design, it can be affected by, speed, change of speed, and wheel weight</li> </ul>                                                                                                                         | <ul style="list-style-type: none"> <li>Road roughness can affect the system.</li> </ul>                                                                                            |

energy. By taking into account the fundamental differences between BEVs and FCEVs, The battery in the FCEV has a lower capacity compared to BEV. Regenerated energy from braking, must be stored in ESS and the smaller battery limits its capacity. Because recovering the energy while it cannot be stored in ESS is pointless. Therefore, further research on co-optimization in CAFHEVs to maximize regenerative braking and improve efficiency presents an interesting area of study. The presence of The FC is an important factor. Using look-ahead data can be used to optimize hydrogen usage as the vehicle can rely on upcoming braking events. In Autonomous FCEV, with the data of upcoming braking events, the FC can be switched off to save fuel. With running on the battery pack, the vehicle can harvest more energy. Since the battery pack will be charged at a predicted point, the vehicle is able to switch from hydrogen to battery. In the next steps, the impact of this approach alongside other factors such as FC health could be investigated. The low temperature in winter affects the capacity of some battery types and this is more important in FCEV with smaller batteries. considering winter conditions in regenerative braking strategies can improve efficiency. Brake strategies for the winter conditions, and using extra harvested energy to heat the battery pack can be investigated in future studies.

**FIGURE 20. Multi-source energy harvesting.**

### C. FUSION OF ENERGY HARVESTING APPROACHES

There are a considerable number of works on RSS, but the number of studies with long-term field test results is limited. The harvesting potential of RSS is lower than regenerative braking. Other methods that were discussed in this paper also have a limited capacity to harvest or recover energy. However, in smart vehicles with varieties of sensors and onboard electronics, every opportunity to increase efficiency should be considered. In this case, applying and operating different harvesting approaches in the vehicle at the same time could be the right spot to conduct more research (Fig. 20). Further research is needed to explore the simultaneous application of multiple energy recovery methods in electric vehicles. While certain methods, such

as solar energy harvesting and regenerative braking, have been commercially implemented [241], the effectiveness and feasibility of combining these techniques with others require in-depth investigation. Specific investigations into the co-existence of different energy recovery methods would greatly contribute to maximizing energy efficiency and optimizing the overall performance of electric vehicles.

## VII. CONCLUSION

Harvesting and recovering energy is an effective approach to extending the range, decreasing fuel consumption, and facilitating the market expansion of BEVs and FCEVs. Different parameters from vehicles and also the environment can affect these harvesting and recovering methods which are presented in Table 7. In the presented review, the energy loss in EVs was investigated and various architectures of BEVs and FCEVs were explored. Energy harvesting technologies and their suitability for various topologies and architectures have been analyzed. ESS can affect the harvesting capability and the combinations of various storage units were studied. Regenerative braking harvests significantly more energy than any other harvesting approach and a comprehensive review of its energy harvesting potentials in EVs was conducted. This harvested energy is heavily dependent on the employed strategy. In addition, the effect of driving patterns on the regenerative brake was studied and the difference between BEV and FCEV was highlighted. With the upcoming autonomous vehicles which are mostly electric, the opportunity to recover energy in this new generation of transportation was discussed. Research on the energy recovery from the suspension system was covered. Energy harvesting in the suspension system is more favorable in heavy vehicles and uneven roads and the price and maintenance cost compared to recovered energy are obstacles to their widespread application. Currently, researchers are more interested in the application of solar harvesting in charging stations but with the increase in solar panels' efficiency, its application in FEVs would be more attractive. We also covered methods to harvest energy from tires, wheels, and other experimental approaches. Finally, the gaps in current works and future trends were analyzed. Using look-ahead technologies and long-term road anticipation in BEVs and FCEVs to optimize regenerative braking and fusion of multiple harvesting methods was suggested for future works. This review can provide a guideline for researchers working on vehicles with clean energy.

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### **2.3 Concluding Remarks**

This review article provided a detailed summary of the current technologies used for energy recovery and harvesting in EVs and FCEVs. It examined various systems, including regenerative braking, thermal energy recovery, and vibration-based energy harvesting, highlighting both their benefits and limitations in practical vehicle applications.

One of the key outcomes of this work is the identification of specific areas where further improvement is needed. These include the need for better integration of multiple energy recovery sources, improved control strategies tailored for hybrid configurations, and more effective use of real-time driving information. It indicates the opportunities that arise from intelligent driving, V2V connectivity, and V2I connectivity. These findings laid the groundwork for the core research in the next chapters.

In the context of this thesis, this review serves as a broad entry point to the subject of energy-efficient driving and powertrain control. It provides the background knowledge necessary to understand the motivations behind the proposed optimization frameworks, especially those targeting fuel efficiency through coordinated control of vehicle speed and power distribution. The next chapters build directly on these insights by presenting original research focused on predictive energy management and optimal speed planning.

## **Chapter 3 - From Sequential to Co-Optimization: Improving Energy Efficiency in Speed Planning and Energy Management**

### **3.1 Introduction**

In this chapter, approaches for improving fuel efficiency through the optimization of speed planning and EMS are presented across two separate articles. The first article of this chapter (the second article in the overall study) examines experimental data to identify limitations in regenerative braking and proposes a method to address these issues. In the second article of this chapter, an integrated method for jointly optimizing speed planning and EMS is introduced (Article 3) and is compared against the sequential method presented in the previous section.

The first article introduces a practical improvement to sequential optimization strategies used in FCEVs, with a specific focus on the speed planning layer. In many existing studies, speed planning is optimized independently of energy management, and regenerative braking limits are typically handled later in the EMS phase. However, this separation can lead to unrealistic or inefficient results, particularly when the speed profile results in regenerative power exceeding the limits of the battery and power electronics. To address this issue, the study proposes the use of a dynamic deceleration constraint during the speed planning stage. Rather than relying on a fixed minimum deceleration rate, the proposed constraint adapts to the vehicle's regenerative power capacity, ensuring that braking events remain within the battery's ability to absorb energy. This approach is especially beneficial under cold-weather conditions, where regenerative capacity is typically reduced. To evaluate the effectiveness of the proposed method, the actual rule-based EMS implemented in the Toyota Mirai is used as a benchmark for comparison. The significance of this article within the thesis lies in its identification of a key limitation

of conventional sequential optimization methods, where speed planning often overlooks critical system-level constraints.

This article presents a unified optimization approach that combines speed planning and energy management into a single optimal control problem for FCEVs. Unlike sequential strategies, where speed planning and energy management are solved separately, this method handles both layers simultaneously. The goal is to improve fuel efficiency by directly incorporating the interactions between vehicle motion and powertrain behavior.

The third article marks a key advancement in the thesis. Building on earlier work, it removes the separation between speed planning and EMS layers and solves the problem within an integrated framework. This framework accounts for detailed vehicle dynamics, battery and fuel cell limits, and electric power losses. The vehicle's speed profile is no longer assumed but is instead optimized along with power distribution, allowing the system to fully benefit from regenerative braking and efficient power usage. The results provide a benchmark for evaluating how much efficiency is lost in sequential methods and offer insights that justify the need for integrated energy-aware driving strategies. This co-optimization approach is central to the thesis, and its structure informs later efforts toward online implementation.

### **3.2 Assumptions**

Throughout this thesis, several assumptions are made. Although these assumptions are stated in each related publication, it is important to clearly summarize them once in this thesis to explicitly define the underlying assumptions and the resulting limitations. These assumptions hold for this chapter as well as for the preceding chapters.

The vehicle–road interaction is modeled under single-lane driving conditions, where

the ego vehicle remains approximately centered within the lane and no lane changes are considered. The wheels are assumed to operate in a near no slip region, with no sustained longitudinal or lateral tire slip. The road is assumed to be unbanked, and lateral dynamics are considered negligible, with side slip assumed to be close to zero and yaw effects neglected.

Regarding the powertrain and energy modeling, the fuel cell is assumed to operate at or near its optimal operating region. In the winter driving scenario, the effect of cold temperature on the initial phase of fuel cell operation is not considered. Mechanical brake blending is not explicitly modeled, and driveline compliance as well as gear dynamics are neglected. Power electronic effects, including converter and inverter switching and conduction losses, are lumped into the electric machine efficiency map.

With respect to sensing, map, and environmental information, road slope, curvature, and GPS pose are assumed to be available, clean, and time-aligned with the simulation grid. The road adhesion coefficient  $\mu$  is assumed to be known or accurately estimated when required. Traffic interactions are limited to car following scenarios, with no cut-ins, overtakes, or multi-agent negotiation considered.

Finally, following a common practice in speed planning studies, a control-oriented model developed for optimization is also used for validation. This choice allows a consistent assessment of the proposed planning and control strategy at the power level. However, while this approach is suitable for power level planning and control, it does not provide detailed system feedback, such as transient and component-level dynamics, that would be captured by a high-fidelity model.

### 3.3 Article 2: The Impact of Dynamic Deceleration Limit on Optimal Speed Planning for Fuel Cell Hybrid Electric Vehicles

Note: In the published version of this article, a typographical error appears in Table 1, where rolling resistance is reported as 0.08. The correct value used in the simulations and analyses is 0.008. This correction does not affect the results or conclusions.

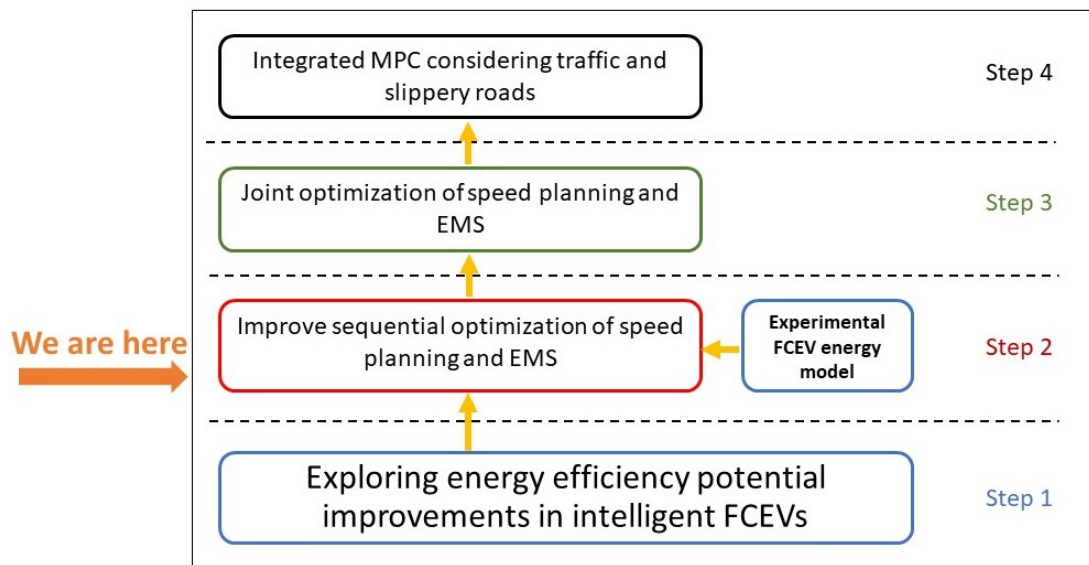


Figure 3.1 The second step in the structure of this work (second article).

# The Impact of Dynamic Deceleration Limit on Optimal Speed Planning for Fuel Cell Hybrid Electric Vehicles

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**Abstract**—Speed profiles and energy management strategy (EMS) significantly influence the energy efficiency of fuel cell hybrid electric vehicles (FCHEVs). Sequential optimization of speed planning and EMS in two layers could be beneficial over co-optimization in terms of computational burden and speed. Traditionally, speed planning is constrained by the electric motor's capabilities, alongside minimum deceleration rates, to ensure safe and realistic vehicle maneuvers. However, these constraints typically overlook the battery and power electronics' capacity to store regenerative power, with power allocation issues being addressed only in the subsequent layer. In response, a new dynamic deceleration rate that incorporates the regenerative capacity limits directly into the speed planning layer has been introduced in this study. The energy efficiency of optimal speed profiles generated using this novel approach is compared with conventional speed profiles under winter conditions, demonstrating enhanced performance and energy recovery.

**Index Terms**—FCHEV, HEV, speed planning, regenerative braking, sequential optimization, Energy Management Strategy, deceleration

## I. INTRODUCTION

Air pollution and fossil fuel concerns have spurred the development of green transport like fuel cell hybrid electric vehicles (FCHEVs). Despite their availability, the limited hydrogen fueling infrastructure highlights the need for improved FCHEV energy efficiency to maximize travel per unit of fuel. The emergence of connected and automated vehicles (CAVs) has facilitated the application of eco-driving and speed planning to save energy [1].

Optimizing energy and fuel consumption is more straightforward in conventional and battery electric vehicles (BEVs) due to a single power source. However, hybrid electric vehicles (HEVs), including FCHEVs, introduce greater complexity.

The energy management strategy (EMS) is crucial for managing fuel consumption in these vehicles and the power demand in EMS is linked to the speed profile. A comprehensive Optimal Control Problem (OCP) adeptly manages HEV speed planning by incorporating all vehicle dynamics and power architecture variables, but this increases computational requirements significantly [2].

To alleviate this issue, scholars have applied sequential optimization methods that address speed planning and EMS optimization in separate layers. In [3], a two-layer optimization method for an FCHEV navigating through signalized intersections is proposed. The upper layer determines the optimal speed trajectory using dynamic programming (DP), while the EMS optimization is addressed using the alternating direction method of multipliers (ADMM). A vehicle-following scenario for fuel cell (FC) trucks was investigated in [4]. The sequential optimization method employed DP for the speed planning and quadratic programming for the energy management part. A convex and integrated co-optimization method was introduced in [5] to reduce power loss due to internal losses of an FCHEV. A decoupled energy management-speed control strategy was studied in [6] to minimize the loss and energy consumption in FCHEVs.

In sequential optimization approaches for FCHEVs, power source limits and specifications are integrated into the EMS layer. Extending these constraints to the speed planning layer could enhance efficiency without significantly increasing computational costs, meriting further exploration. This study aims to address this integration and assess potential improvements in energy recovery. By incorporating autonomous driving technologies, sensors, available road data, and the vehicle's performance limitations, the speed profile is enhanced to highlight its potential for energy savings.

The structure of this paper includes an introduction to the main problem, followed by an exploration of speed planning optimization and an examination of the EMS. Results and concluding remarks are presented in the final section.

## II. BACKGROUND AND PROBLEM DEFINITION

The vehicle model examined in this study is designed to represent a general (light-duty vehicle) LDV and features an FC and battery as the main and secondary power source depicted in Fig. 1. Table 1 lists the main characteristics of the vehicle. In the presented study, a trip between two stops for a distance of 1000 m on a straight and flat road is considered and the trip must be finished in  $T$  seconds. In this work, road traffic is not considered; consequently, the vehicle's speed is not influenced by the behavior of other road users or by infrastructure elements such as traffic lights. By considering a straight and flat road, we simplify the model, allowing us to break down and analyze the effects of various factors more clearly. Additionally, any arbitrary path can ultimately be represented as a series of connected straight segments, making our findings broadly applicable. It is assumed that the trip is completed in an autonomous mode.

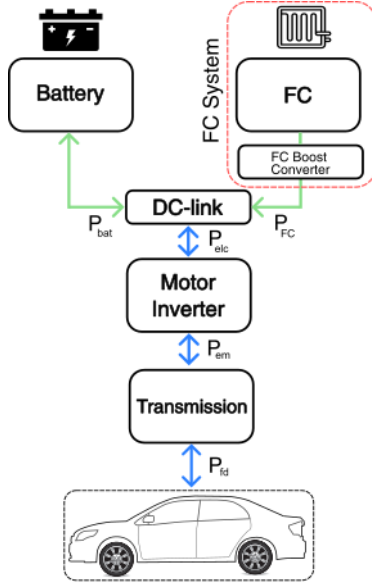


Fig. 1. Block diagram of FCHEV power train used in this work.

The capacity of the secondary power source to store regenerated energy significantly enhances energy recovery [7]. Publicly available dynamometer test results for the 2017 Toyota Mirai from Argonne National Laboratory help analyze specific limits [8]. Figure 2 demonstrates how battery constraints limit regenerated power, highlighting potential power losses when speed control and energy management are decoupled. Incorporating these braking limits into the speed planning OCP can minimize losses associated with battery constraints.

TABLE I  
VEHICLE MAIN CHARACTERISTICS BASED ON MIRAI

| symbol      | description         | value                          |
|-------------|---------------------|--------------------------------|
| $m$         | 1940 kg             | vehicle mass                   |
| $\mu_{rr}$  | 0.08                | rolling resistance coefficient |
| $C_D$       | 0.29                | aerodynamics drag coefficient  |
| $A$         | 2.38 m <sup>2</sup> | frontal area                   |
| $r_{wh}$    | 0.371 m             | wheel radius                   |
| $fd$        | 3.478               | final drive ratio              |
| –           | 113 kW              | maximum FC output power        |
| $Q_{bat}$   | 6 Ah                | battery capacity               |
| $\eta_{fd}$ | 0.98                | final drive efficiency         |

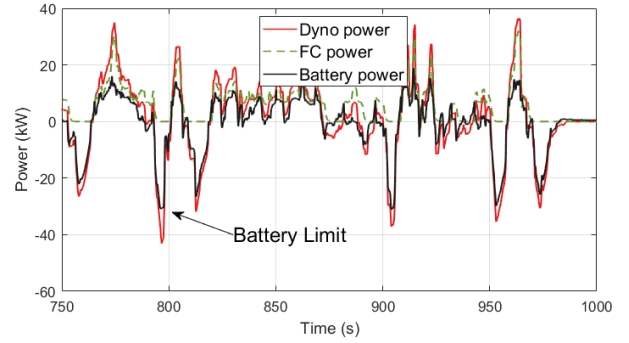


Fig. 2. The experimental data from [8] indicates the limit on the regeneration power imposed by the battery.

## III. VEHICLE MODEL

### A. Vehicle Dynamics Model

The longitudinal dynamics of the vehicle are characterized by the following:

$$m \frac{dv}{dt} = F_v(t) - F_{res}(t) \quad (1)$$

In this equation,  $m$  is the total effective mass. The  $F_v$  is the driving force of the vehicle (at the wheel), which is positive during traction (when energy is transferred from the powertrain to the vehicle) and negative during braking. The  $F_{res}$  includes three components and it can be shown as:

$$f_{res} = 0.5\rho_a A C_D (v)^2 + mg \cos(\theta) C_{rr} + mg \sin(\theta) \quad (2)$$

where  $C_{rr}$  is the coefficient of rolling resistance,  $A$  is vehicle front area,  $C_D$  is drag coefficient,  $\rho_a$  is air density ( $1.225 \text{ kg/m}^3$ ),  $g$  is the gravitational constant ( $9.81 \text{ m/s}^2$ ),  $\theta$  is road grade in radians, and  $v$  is vehicle speed ( $\text{m/s}$ ). The total wheel power can be calculated as:

$$P_v = F_v v \quad (3)$$

Wheel power and the output of the final drive are equal in traction mode ( $P_v = P_{fd}$ ). If the mechanical brakes are not

considered, the regeneration mode would be the same. If the mechanical brakes,  $P_{\text{brake}}$ , are applied:

$$P_{\text{fd}} = P_v - P_{\text{brake}} \quad (\forall P_v < 0) \quad (4)$$

The mechanical brake is considered a power withdrawal and it is always a negative value. In this study, the braking distribution between the rear and front axles is not considered and it is assumed regenerative power is not limited by it. The connection of bidirectional power flow between electric motor (EM) mechanical power,  $P_m$ , and final drive output can be modeled as:

$$P_{\text{fd}} = \eta_{\text{fd}}^{\text{sign}(P_m)} P_m \quad (5)$$

$$P_m = \tau_{\text{em}} \omega_{\text{em}} \quad (6)$$

With the efficiency of the final drive, denoted as  $\eta_{\text{fd}}$ , treated as a constant, and  $\tau_{\text{em}}$  representing the load torque and  $\omega_{\text{em}}$  the rotational speed of the EM, the relationship between the EM's rotational speed and the wheel's rotational speed ( $\omega_{\text{wheel}}$ ) is given by the following equation:

$$\omega_{\text{em}} = \frac{v \cdot fd}{r_{\text{wh}}} \quad (7)$$

$$\omega_{\text{wheel}} = \frac{\omega_{\text{em}}}{fd} \quad (8)$$

where the  $fd$  stands for the final drive ratio and  $r_{\text{wh}}$  is wheel radius. In addition the relation between  $F_v$  and  $\tau_{\text{em}}$  is represented as :

$$F_v = \frac{\tau_{\text{em}} \cdot fd \cdot \eta_{\text{fd}}^{\text{sign}(\tau_{\text{em}})}}{r_{\text{wh}}} \quad (9)$$

The physical limits of the electric motor (EM) are crucial to consider. Specific data on the electric motor of an FCHEV like the Toyota Mirai is not readily available. However, as mentioned in [5], scaling up the motor map of the Toyota Prius can be used as a reference. The boundaries on maximum torque ( $\tau_{\text{max}}$ ) can be described as a second order approximation:

$$\tau_{\text{max}} = \min(340, av^2 + bv + c) \quad (10)$$

The electric power supplied to or generated by the motor, including its inverter is represented as  $P_{\text{elc}}$  in efficiency as a function of motor torque and rotational speed. In this study for simplicity, the EM efficiency is considered a constant value. The model for power flow with a combined motor-inverter can be expressed as:

$$P_m = \eta_{\text{em}}(\tau, \omega)^{\text{sign}(P_{\text{elc}})} P_{\text{elc}} \quad (11)$$

In this study, the power generated by the FC ( $P_{\text{fc}}$ ) and the battery ( $P_{\text{bat}}$ ) are integrated at the DC-link. An FC system, which includes a boost converter, is considered and will be detailed in the following subsection. The relationship between the hydrogen chemical power ( $P_{\text{H}_2}$ ) and the efficiency of the FC ( $\eta_{\text{fc}}$ ) is demonstrated as follows:

$$P_{\text{fc}} = P_{\text{H}_2} \eta_{\text{fc}} \quad (12)$$

resulting in the following balance:

$$P_{\text{elc}} = P_{\text{fc}} \eta_{\text{conv}} + P_{\text{bat}} \quad (13)$$

$\eta_{\text{conv}}$  represents the efficiency of converter.

## B. Primary Power Source: Fuel cell

Black box models of FC require low computational effort and are particularly well-suited for applications such as vehicles [9], [10]. The FC efficiency ( $\eta_{\text{fc}}$ ) could be described as a function of FC power,  $P_{\text{fc}}$ . Developing the hydrogen consumption model of Toyota Mirai using data presented in [8] has been discussed in [5], [11]. The hydrogen flow rate can be formulated as :

$$\dot{m}(t) = \frac{P_{\text{fc}}(t)}{LHV_{\text{H}_2} \times \eta_{\text{fc}}} \quad (14)$$

Where  $LHV_{\text{H}_2}$  is the lower heating value of hydrogen.

## C. Secondary Power Source: Battery

The battery model of the Toyota Mirai has been studied in this work. The terminal voltage  $V_t$  of the battery is governed by an equivalent circuit model including open-circuit voltage  $V_{\text{oc}}$ , the internal resistance  $R_b$ , and current  $I_b$ :

$$V_t = V_{\text{oc}} - I_b R_b \quad (15)$$

The parameters to obtain  $V_{\text{oc}}$  and  $R_b$  based on Toyota Mirai's data are discussed in [11]. The *SOC* change rate is calculated as follows:

$$\dot{SOC} = -\frac{I_b \eta_{\text{bat}}^{\text{sign}(I_b)}}{Q_{\text{bat}}} \quad (16)$$

The  $\eta_{\text{bat}}$  is coulomb efficiency and in this study is considered 0.98 and  $Q_{\text{bat}}$  represents the battery capacity. The battery current is calculated based on the battery power demand ( $P_{\text{bat}}$ ):

$$I_b = \frac{V_{\text{oc}} - \sqrt{V_{\text{oc}}^2 - 4R_b P_{\text{bat}}}}{2R_b} \quad (17)$$

## IV. OPTIMAL SPEED PLANNING

This section addresses the optimal control problem related to speed planning for an FCHEV. The first layer concentrates on determining the optimal speed trajectory that minimizes the total power required for the vehicle to travel the distance between two stops ( $l$ ) in a given time ( $T$ ). The cost function is defined as:

$$J = \int_0^T P_v dt \quad (18)$$

The state space model with speed and distance ( $s$ ) as state variables can be shown as:

$$\frac{d}{dt} \begin{pmatrix} s \\ v \end{pmatrix} = \begin{pmatrix} v \\ \frac{1}{m} (F_v - F_{\text{res}}) \end{pmatrix} \quad (19)$$

The one input is  $F_v$ . The vehicle speed is constrained to legal speed in an urban area ( $v_{\text{max}}$ ):

$$0 \leq v \leq v_{\text{max}} \quad (20)$$

The boundary conditions for the problem are :

$$s(0) = 0, s(T) = l, \quad (21)$$

$$v(0) = v(T) = 0, \quad (22)$$

During the EM operation, the torque should not exceed the maximum allowed torque discussed in (12). This will ensure the assignment of realistic control input. The other common constraint on the vehicle maneuver is acceleration and deceleration rate which affect the ride comfort greatly. The constraint on the acceleration and deceleration is expressed as:

$$\begin{cases} a > a_{\min} \\ a < a_{\max} \end{cases} \quad (23)$$

However, as discussed earlier, the amount of regenerative power that the battery can absorb is limited, dependent on the battery and power electronics specifications. Under typical weather conditions for the Mirai, the power limit  $P_{\lim}$  is 30 kW. Considering winter conditions, particularly at temperatures around  $-10^\circ\text{C}$ , this limit decreases by 15 percent [12]. Therefore, assuming a  $P_{\lim}$  of 25 kW is realistic for a normal winter in areas like Canada. It is assumed that the power limit remains static and is unaffected by the battery's SOC or other factors, such as battery aging. In regeneration mode, a new deceleration term can be defined as a dynamic term:

$$a_{\text{dec}} = \frac{P_{\lim}}{mv\eta_{fd}\eta_{em}} \quad (24)$$

The term  $a > a_{\min}$  can be replaced by an updated constraint:

$$a > a_{\text{dec}} \quad (25)$$

In addition, when the vehicle speed drops below the vehicle minimum regenerative limit ( $v_{\lim}$ ), regenerative braking is not efficient and it is unnecessary to optimize the regenerative braking [7]. The ( $v_{\lim}$ ) have been considered 2.5 m/s. The  $a_{\text{dec}}$  can be rewritten as:

$$a_{\text{dec}} = \begin{cases} a_{\min} & \text{if } v < v_{\lim} \\ \max\left(a_{\min}, \frac{P_{\lim}}{mv\eta_{fd}\eta_{em}}\right) & \text{otherwise} \end{cases} \quad (26)$$

The formulated optimal control problem is addressed by IPOPT solver, using CasaDi which is a MATLAB-based software framework for nonlinear optimization and optimal control problems [13]. Fig. 3 compares the result of the optimized speed trajectory using IPOPT (with  $a_{\text{dec}}$  corresponding to  $P_{\lim}$  of 30 kW) and conventional speed profile using only  $a_{\min}$  to limit deceleration for a vehicle with regenerative braking.

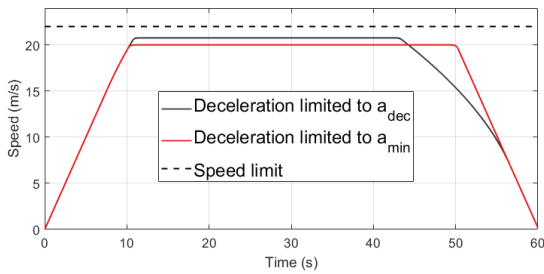


Fig. 3. Comparison between speed profile constrained with  $a_{\min}$  and speed profile constrained with  $a_{\text{dec}}$ .

Fig. 4 illustrates the optimal speed trajectories for varying  $a_{\text{dec}}$  corresponding to  $P_{\lim}$  levels, specifically at 25 kW, 30 kW, 35 kW, 40 kW, and 45 kW. When the deceleration is limited to  $a_{\text{dec}}$  corresponding to 25 kW, braking initiates earlier to adhere to the power constraint.

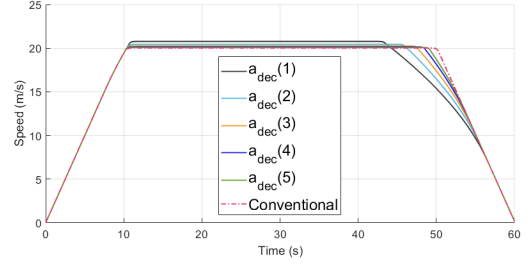


Fig. 4. Optimal speed trajectories for considering:  $a_{\text{dec}}(1)$  for  $P_{\lim}$  of 25 kW,  $a_{\text{dec}}(2)$  for  $P_{\lim}$  of 30 kW,  $a_{\text{dec}}(3)$  for  $P_{\lim}$  of 35 kW,  $a_{\text{dec}}(4)$  for  $P_{\lim}$  of 40 kW,  $a_{\text{dec}}(5)$  for  $P_{\lim}$  of 45 kW, and conventional optimal speed profile using  $a_{\min}$ .

## V. ENERGY MANAGEMENT STRATEGY

In this study, the focus is on the impact of speed planning, thus a rule-based EMS approach is suitable for our needs. A rule-based EMS that replicates the Toyota Mirai's actual EMS is adopted from [11] to develop our EMS layer. In this strategy, the FC operates under two main conditions: first, Idle, where no power is delivered. The second is active, where power is delivered in response to the motor's power demand. Switching between active and idle states is decided by the  $P_{\text{on}}(\text{SOC})$  and  $P_{\text{idle}}(\text{SOC})$  that are a function of SOC. In the activation zone the  $P_{\text{fc}}$  can be calculated as follows:

$$P_{\text{fc}} = \begin{cases} P_{\text{low}}(P_{EM}) & \text{if } \text{SOC} > 55.25, \\ P_{\text{mid}}(P_{EM}) & \text{if } 54.75 < \text{SOC} < 55.25, \\ P_{\text{hi}}(P_{EM}) & \text{if } \text{SOC} < 54.75, \end{cases} \quad (27)$$

$P_{\text{hi}}$  and  $P_{\text{low}}$  are function of demanded power (which is equal to  $P_{\text{elc}}$ ), and  $P_{\text{mid}}$  is represented as :

$$P_{\text{mid}} = P_{\text{low}} + (P_{\text{hi}} - P_{\text{low}}) \frac{\text{SOC} - 54.75}{55.25 - 54.75} \quad (28)$$

After calculating the FC power  $P_{\text{fc}}$ ,  $P_{\text{bat}}$  and dissipated power  $P_{\text{dis}}$  are calculated base on :

$$P_{\text{elc}} = P_{\text{bat}} + P_{\text{fc}} + P_{\text{dis}} \quad (29)$$

As mentioned, under winter conditions, it is assumed that the battery and power electronics cannot handle regenerative power levels over  $P_{\text{elc}} = 25\text{kW}$  ( $P_{\text{elc}} < -25\text{kW}$ ), necessitating the dissipation of excess power. To compare the outcomes in terms of regenerated power and hydrogen consumption, the optimized speed profiles with  $a_{\text{dec}}$  corresponding to  $P_{\lim}$  of 25 kW and 45 kW, along with a conventional optimized speed profile, are utilized. The results of FC power, battery power, and dissipated power are compared in Fig. 5.

Table 2 presents the hydrogen consumption, dissipated energy, regenerative energy fed to the battery, and SOC during the trip.

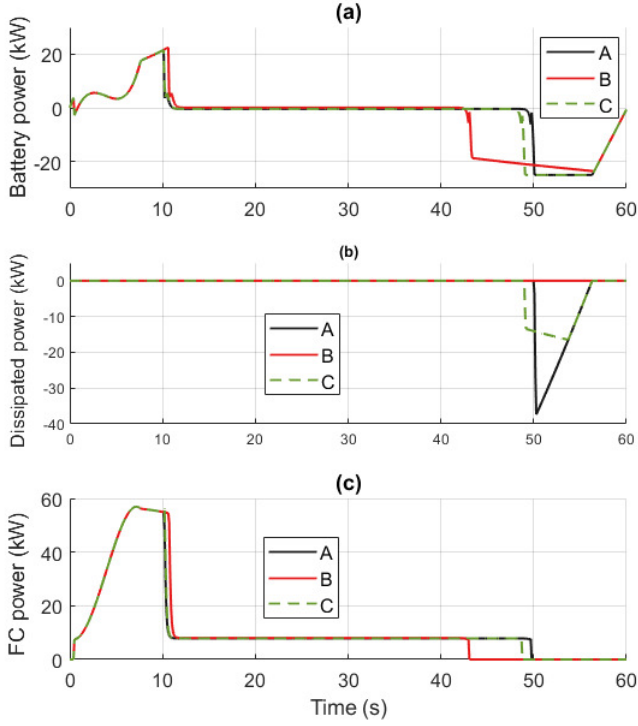


Fig. 5. (a) Battery power over time, (b) dissipated power over time, and (c) FC power over time. (A) represents conventional optimal speed profile, (B) represents speed profile with  $a_{dec}$  for  $P_{lim}$  of 25 kW, and (C) represents speed profile for  $P_{lim}$  of 45 kW.

TABLE II  
VEHICLE MAIN CHARACTERISTICS

|                      | Speed profiles based on the use of |                   |                   |
|----------------------|------------------------------------|-------------------|-------------------|
|                      | $a_{min}$                          | $a_{dec}$ @ 45 kW | $a_{dec}$ @ 25 kW |
| Final SOC            | 59.1                               | 59.5              | 60.7              |
| Dissipated energy    | 119 kJ                             | 91 kJ             | 0 kJ              |
| Recovered energy     | 223 kJ                             | 247 kJ            | 326 kJ            |
| Hydrogen consumption | 9.7 g                              | 9.6               | 9.5 g             |

The optimized speed profile, utilizing a dynamic deceleration rate,  $a_{dec}$ , adjusted to the actual energy storage capacity of 25 kW, results in lower fuel consumption and no energy dissipation. Even when considering an inaccurate energy storage limit—such as tuning  $a_{dec}$  based on a  $P_{lim}$  of 45 kW—using  $a_{dec}$  still proves advantageous over  $a_{min}$ . Calculations show that the speed profile derived using  $a_{min}$  yields the poorest performance in terms of energy recovery and fuel efficiency.

The dynamic deceleration effectively maintains regenerative power within the battery's charge limit, thereby minimizing dissipated power. By closely aligning the dynamic deceleration limit with the actual battery limits (25 kW in this study)

the regenerated braking power consistently stays within the battery's absorption capacity, eliminating energy dissipation. Our findings indicate that even when dynamic deceleration does not strictly adhere to the battery's exact limits, it remains advantageous. For instance, in the case study presented, speed planning with a fixed deceleration limit generated approximately a peak power of 60 kW of regenerative power. Such a high peak power is beyond the capacity of the battery to absorb and it increases the aging of the battery and poses significant challenges to its overall lifespan. However, implementing a dynamic deceleration limit of 45 kW still significantly reduced power loss. To respect this limit vehicle starts decelerating sooner, which means staying more time in the acceptable regenerative power zone and dissipating less energy through mechanical brakes.

## VI. CONCLUSION

In the sequential optimization of speed planning and EMS for HEVs such as FCHEVs, constraining the speed planning OCP by electric motor limits, maximum acceleration, and minimum deceleration rates ensures realistic vehicle maneuvers. However, this approach often overlooks the limits of battery and power electronics to absorb regenerative energy, as power allocation is typically addressed in the EMS layer. A shift from a fixed deceleration constraint ( $a_{min}$ ) to a dynamically calculated deceleration rate constraint ( $a_{dec}$ ), which is tuned based on the known regenerative power absorption limits, led to the development of a new speed profile. Although the total energy required to complete a simulated trip was nearly identical when considering only the speed planning layer, significant improvements were observed in the recovery of regenerative energy when integrating the EMS layer. The proposed speed profile effectively reduced the energy loss due to excessive regenerative power to zero. By implementing  $a_{dec}$  hydrogen consumption was reduced by 2 percent, while recovered energy saw a significant increase of 46 percent. Moreover, the study demonstrated that even with a highly inaccurate assumption of  $P_{lim}$  for calculating  $a_{dec}$ , fuel consumption and energy losses were decreased compared to conventional optimal speed profiles.

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### 3.4 Article 3: Fuel Efficiency Through Co-Optimization of Speed Planning and Energy Management in Intelligent Fuel Cell Electric Vehicles

Note: In the published version of this article, a typographical error appears in Table 1, where rolling resistance is reported as 0.08. The correct value used in the simulations and analyses is 0.008. This correction does not affect the results or conclusions.

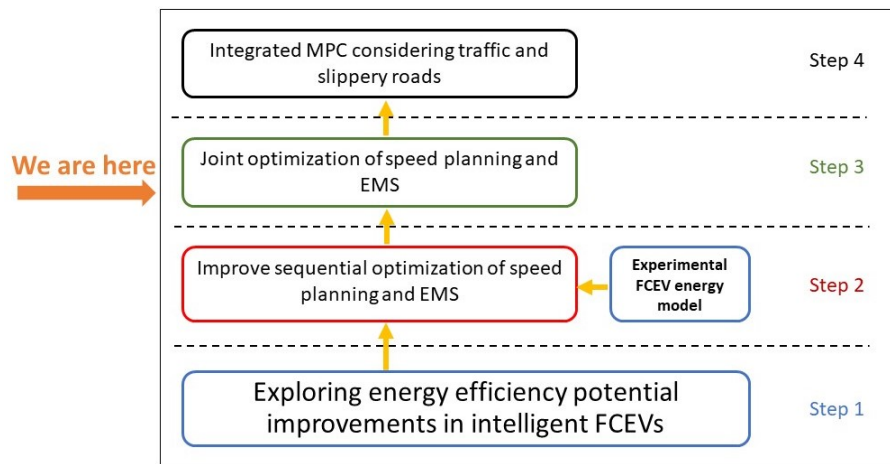
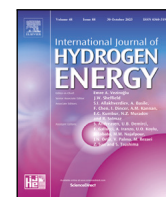


Figure 3.2 Visual presentation of the third step in this study



# Fuel efficiency through co-optimization of speed planning and energy management in intelligent fuel cell electric vehicles

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## ABSTRACT

Fuel cell electric vehicles (FCEVs) offer a promising path to sustainable transportation, but their full potential depends on an effective energy management strategy (EMS). Intelligent driving offers an opportunity to integrate speed planning with EMS for improved efficiency. This study proposes a co-optimization framework that jointly optimizes speed planning and EMS for intelligent FCEVs. An energy model for the Toyota Mirai is developed and validated using real-world test data. The formulated optimal control problem (OCP) minimizes hydrogen consumption, effectively avoids power peaks, and maximizes regenerative braking by considering battery and electric motor constraints when planning deceleration. The proposed method is evaluated against widely studied sequential optimization approaches. On a flat road with a 1000-m look-ahead window, it achieves a 25% reduction in fuel consumption. Under realistic conditions with varying speed limits and slopes, it reduces hydrogen consumption from 39 g to 24.46 g, achieving a 36% improvement and a smoother power profile.

## 1. Introduction

Current concerns about sustainable energy policies and environmental issues have pushed the market toward new energy vehicles, such as battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs). FCEVs offer emission-free driving and fast refueling times. However, the limited availability of hydrogen refueling infrastructure remains a significant obstacle to the widespread adoption of this technology. Improving energy efficiency in FCEVs could play a key role in overcoming this challenge [1,2].

Optimizing driving behavior and vehicle speed is crucial for the deep optimization of vehicle energy consumption [3]. One approach to improving energy efficiency is adopting an energy-efficient driving style called eco-driving. Eco-driving techniques include practices that follow speed profiles to reduce energy consumption over a trip and can be formulated as an optimal control problem (OCP) by considering energy demand at the wheels. For instance, in conventional vehicles, pulse-and-glide speed profiles, which include rapid acceleration followed by a coasting phase, are more efficient [4]. Electric vehicles that have the advantage of regenerative braking could benefit from a different speed profile, as they can recover braking energy [5]. In [6], optimal speed profiles for conventional vehicles, HEVs, and EVs were

discussed and compared extensively. Some studies have used traffic information to adopt an optimal speed for navigation through intersections and traffic lights [7,8]. In [9], the proposed method integrates a server-side planner for large-scale speed optimization and vehicle-side controllers for real-time execution. In [10], a learning-based speed planning approach is proposed to address eco-driving for connected electric buses. For a more detailed review of extensive studies on speed planning, readers are referred to [11].

With autonomous driving on the horizon, new opportunities have emerged to reduce fuel consumption. Advances in sensor technology and the implementation of connected vehicles add an extra layer of information, enabling the development of energy-efficient autonomous driving approaches. A unique advantage of automated driving is its ability to produce and adhere to energy-optimal speed profiles, which is nearly impossible for human drivers who cannot consistently follow optimal profiles or anticipate events beyond their line of sight. However, if finding the optimal speed profile does not extend to cover energy sources, there would be no difference between a BEV and an FCEV.

To address the unique characteristics of powertrains in FCEVs and HEVs to reduce fuel consumption, numerous studies have focused on energy management strategies (EMS). HEVs and FCEVs, which typically incorporate two or more power sources, rely on EMS to

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## Nomenclature

|                  |                                     |
|------------------|-------------------------------------|
| $\dot{m}_H$      | Hydrogen mass flow rate             |
| $\eta_{bat}$     | Battery efficiency                  |
| $\eta_{fd}$      | Final drive efficiency              |
| $\mu_{rr}$       | Rolling resistance coefficient      |
| $\omega_{em}$    | Electric motor speed                |
| $\omega_{wheel}$ | Wheel rotational speed              |
| $\tau_{em}$      | Electric motor torque               |
| $\theta$         | Road grade                          |
| $A$              | Frontal area                        |
| $a_x$            | Longitudinal acceleration           |
| $a_y$            | Lateral acceleration                |
| $C_D$            | Aerodynamic drag coefficient        |
| $F_v$            | Driving force at the wheel          |
| $F_{res}$        | Total resistance force              |
| $fd$             | Final drive ratio                   |
| $I_b$            | Battery current                     |
| $LHV_{H_2}$      | Lower heating value of hydrogen     |
| $m$              | Vehicle mass                        |
| $P_m$            | Mechanical power of the motor       |
| $P_v$            | Wheel power                         |
| $P_{bat}$        | Battery power                       |
| $P_{brake}$      | Mechanical brake power              |
| $P_{elc}$        | Electric power                      |
| $P_{fc}$         | Fuel cell power                     |
| $P_{fd}$         | Power at final drive output         |
| $Q_{bat}$        | Battery capacity                    |
| $R_b$            | Internal resistance of the battery  |
| $r_{wh}$         | Wheel radius                        |
| $s$              | Traveled distance                   |
| $SOC$            | State of charge of the battery      |
| $T$              | Total travel time                   |
| $v$              | Vehicle speed                       |
| $V_{oc}$         | Open-circuit voltage of the battery |

determine the optimal power allocation between these sources to minimize fuel consumption. Various methods have been employed for EMS, including rule-based approaches [12–14], optimization-based approaches [15–17], and learning-based approaches [18–20]. In [21], an EMS is evaluated using three control approaches. In [22], a reinforcement learning-based energy management strategy is refined to improve fuel efficiency and vehicle dynamics. An extensive review of energy management strategies for FCEVs is presented in [23]. Most of these studies on FCEVs focus exclusively on the EMS layer and tank-to-wheel efficiency, without integrating speed profile optimization. Some studies have employed speed prediction to enhance EMS performance [24,25]. Ma et al. [26] propose a real-time EMS for FCHEVs, integrating a variable horizon velocity prediction method to enhance Pontryagin's Minimum Principle-based optimization. Authors in [27] develop a predictive EMS for fuel cell hybrid buses, incorporating speed and passenger flow predictions using bi-directional Long Short-Term Memory networks. Kofler et al. [28] propose a predictive EMS for fuel cell vehicles, using route-based long-term power demand predictions to optimize the SoC trajectory.

For FCEVs, some studies have attempted to optimize speed planning and EMS sequentially, which provides solutions by considering tank-to-wheel and wheel-to-distance efficiencies separately. In this approach, speed planning and EMS are optimized hierarchically and are more effective than optimizing EMS and excluding speed. Vehicle dynamics and road data are used to find an optimal speed profile, which

then serves as an input for energy management optimization. In [3], a bi-level method was presented to solve the speed planning problem and EMS for FCEVs traveling through signalized intersections. In another attempt to address signalized intersections for FCEVs, Liu et al. [29] proposed a convex bi-level optimization. This method did not consider regenerative braking limits and included simplifications to achieve convexity. In [30], speed planning, EMS, and an energy recovery module were optimized sequentially for an FCEV in dynamic urban traffic scenarios. This work was extended in [31] to include dynamic curving scenarios. A convex bi-level optimization for FCEVs was proposed in [32], considering electric motor losses, final drive losses, and fuel cell (FC) efficiency. This method worked well for online applications; however, because of the split nature of the bi-level problem, improvements in speed profiles and energy consumption were limited and sub-optimal. A two-layered optimization for a fleet of FC trucks was discussed in [33]. Ref. [34] introduces a centralized spacing control strategy for connected and automated FCEV platoons, using gradient-based model predictive control. Ref. [35] develops a hierarchical control-based energy management strategy for FCHVs, integrating nonlinear MPC and a multi-objective energy management system. Zhang et al. [36] propose a hierarchical eco-driving control strategy for connected HEVs, integrating predictive cruise control with an EMS based on cost-to-go approximation. In another study considering car-following scenarios [37], a hierarchical strategy integrates eco-driving and energy management for hybrid electric vehicles. Despite the popularity of sequential optimization methods to handle complex driving scenarios, the separated nature of this approach results in suboptimal solutions, as the power sources do not directly affect the speed profile [38].

For further improvement, some studies integrate the speed planning layer and EMS into a comprehensive problem to find optimal speed and power allocation simultaneously as co-optimization. This approach results in a more complex problem that demands higher computational effort. A joint optimization of speed and energy management was introduced in [39] for series HEVs, with results compared to a hierarchical framework for the optimal control problem. The joint optimization outperformed the sequential method. In [40], a data-driven approach was proposed for eco-driving and energy management strategy optimization of a plug-in HEV to reduce computational effort. However, this method heavily relies on high-quality data sets for training neural networks, and if these data sets do not represent diverse real-world scenarios, their performance could degrade. In [41], the authors present a cooperative optimization framework that integrates Adaptive Cruise Control and EMS using a Soft Actor-Critic algorithm for an FCEV in a car following scenario. In another work focused on car following driving, Chen et al. proposed an integrated eco-driving framework for FCHEVs that optimizes speed and energy management collaboratively, using a deep deterministic policy gradient-based algorithm [42]. In [43], a sequential optimization was compared to co-optimization for an FCEV using dynamic programming. While the superior performance of co-optimization in an FCEV was demonstrated, the complexity of the problem was reduced by limiting the control actions as the input controls were simplified into five modes (e.g., full regenerative braking, full braking, coasting, cruising, and full propulsion), which could be unrealistic. Additionally, model simplifications, such as ignoring electric motor losses, affected the results. An analytical method for the co-optimization of speed planning and energy management in automated Parallel HEVs at multi-signal intersections was developed in [44].

Another challenge affecting studies on EMS and speed optimization for FCEVs is the lack of realistic and validated components in the vehicle models used. For instance, comparing characteristics such as the FC maximum power and battery capacity of a commercial FCEV like the Toyota Mirai with the vehicle models in [3,29,30,43] reveals a considerable gap between the models and real-world applications.

Overall, studies that focus solely on the EMS layer without speed optimization overlook the advantages of intelligent driving in FCEVs.

Sequential approaches that optimize speed planning and EMS separately lead to suboptimal solutions. Finally, existing co-optimization studies often rely on simplifications, lack a dedicated focus on FCEVs, and do not incorporate real-world data. Currently, there is a lack of studies on the energy-saving potential of intelligent FCEVs that integrate speed profile optimization and EMS into a unified framework supported by experimental data. This study contributes to autonomous FCEV research in the following ways:

1. We propose an integrated framework for FCEVs to simultaneously optimize the speed profile and power allocation, addressing gaps in prior studies. Extracted road data and mission information are used in an OCP, where the vehicle's motion model and powertrain model are integrated as a co-optimization problem. Here, speed and EMS are controlled smoothly using vehicle jerk and dynamic jerk equivalents for the battery and FC to minimize the total hydrogen consumption over a mission.
2. The vehicle parameters and component modeling in this study are derived from a commercial FCEV (Toyota Mirai) using real-world experimental test data, ensuring the results accurately reflect realistic conditions and system behavior.
3. Constraints on the energy sources and electric motor are incorporated into the optimal control problem to maximize regenerated energy and eliminate energy losses caused by speed profiles that exceed the battery charging limit and the motor's braking power. This approach results in speed profiles that optimize energy recovery throughout the trip.

The rest of this paper is structured as follows. Section 2 introduces the vehicle and powertrain models. Section 3 describes the proposed co-optimization control strategy and provides the formulations for both conventional sequential optimization and an improved version for comparison. Section 4 presents three case studies, where the results of the described methods are compared. Finally, Section 5 concludes the presented work.

## 2. Problem definitions and modeling

In this study, an intelligent FCEV equivalent of a level 3 autonomous general light-duty vehicle is considered for driving tasks. A level 3 autonomous vehicle can handle all driving aspects in well-mapped environments, but the driver must be ready to take control upon request [45]. The vehicle features a FC as the main power source and a battery as the secondary power source, as depicted in Fig. 1. The proposed approach in this work addresses both tank-to-wheel and wheel-to-distance efficiencies. The power source, powertrain, and general vehicle specifications are modeled and selected based on the 2017 Toyota Mirai, which serves as the target vehicle [46]. Table 1 lists the main characteristics of the Mirai.

The main goal of this study is to solve a free-driving problem to achieve minimum fuel consumption for completing a trip that starts from a start point and ends at a designated destination. The trip is defined by the route and travel time. In this study, traffic conditions are not considered, and the vehicle's speed is not influenced by the behavior of other vehicles on the road. This approach has the potential to be extended to other scenarios, such as navigating signalized intersections or car-following situations.

### 2.1. Vehicle model

The longitudinal dynamic equation of the vehicle is shown by the following [4]:

$$m \frac{dv}{dt} = F_v - F_{\text{res}} \quad (1)$$

In this equation,  $m$  is the total mass.  $F_v$  is the vehicle's driving force (at the wheel), which is positive during traction (when energy

**Table 1**

Vehicle main characteristics based on the data from [46] and [32].

| Symbol           | Description                    | Value               |
|------------------|--------------------------------|---------------------|
| $m$              | Vehicle mass                   | 1940 kg             |
| $\mu_{rr}$       | Rolling resistance coefficient | 0.08                |
| $C_D$            | Aerodynamics drag coefficient  | 0.29                |
| $A$              | Frontal area                   | 2.38 m <sup>2</sup> |
| $r_{wh}$         | Wheel radius                   | 0.371 m             |
| $fd$             | Final drive ratio              | 3.478               |
| –                | Maximum FC output power        | 114 kW              |
| $Q_{\text{bat}}$ | Battery capacity               | 6 Ah                |
| $\eta_{fd}$      | Final drive efficiency         | 0.97                |

is transferred from the powertrain to the vehicle) and negative during braking. The  $F_{\text{res}}$  represents resistance forces and includes three parts and it can be expressed as [4]:

$$F_{\text{res}} = 0.5\rho_a AC_D(v)^2 + mg \cos(\theta)C_{rr} + mg \sin(\theta) \quad (2)$$

where  $C_{rr}$  represents the rolling resistance coefficient,  $A$  is the frontal area of the vehicle,  $C_D$  denotes the drag coefficient,  $\rho_a$  is the air density (1.225 kg/m<sup>3</sup>),  $g$  is the gravitational constant (9.81 m/s<sup>2</sup>),  $\theta$  is the road grade in radians, and  $v$  is the vehicle speed in meters per second (m/s). The total wheel power can be determined as follows:

$$P_v = F_v v \quad (3)$$

Wheel power and the output of the final drive are equal in traction mode ( $P_v = P_{fd}$ ). If the mechanical brakes are not considered, and in a pure regeneration mode it would be the same in the braking. If the mechanical brakes,  $P_{\text{brake}}$ , are considered:

$$P_{fd} = P_v - P_{\text{brake}} \quad (\forall P_v < 0) \quad (4)$$

The mechanical brake is treated as a power loss, which yields a negative value consistently. In this study, the distribution of braking force between the rear and front axles is not considered, and it is assumed that regenerative power is not constrained by this factor. The bidirectional power flow connection between the electric motor's mechanical power,  $P_m$ , and the final drive output can be modeled as:

$$P_{fd} = \eta_{fd}^{\text{sign}(P_m)} P_m \quad (5)$$

$$P_m = \tau_{em} \omega_{em} \quad (6)$$

Assuming a constant final drive efficiency,  $\eta_{fd}$ , with  $\tau_{em}$  as the load torque and  $\omega_{em}$  as the electric motor's rotational speed, the relationship between the electric motor's rotational speed and the wheel's rotational speed ( $\omega_{\text{wheel}}$ ) is given by the following equation:

$$\omega_{em} = \frac{v \cdot fd}{r_{wh}} \quad (7)$$

$$\omega_{\text{wheel}} = \frac{\omega_{em}}{fd} \quad (8)$$

where  $fd$  stands for the final drive ratio and  $r_{wh}$  is the wheel radius. In addition, the relation between  $F_v$  and  $\tau_{em}$  is represented as:

$$F_v = \frac{\tau_{em} \cdot fd \cdot \eta_{fd}^{\text{sign}(\tau_{em})}}{r_{wh}} \quad (9)$$

Considering the physical limits of the electric motor (EM) is essential, as the maximum motor torque restricts the vehicle's performance in both acceleration and regeneration modes. While specific data on the electric motor of an FCEV such as the Toyota Mirai are limited, [32] suggests using a scaled-up motor map of the Toyota Prius as a reference, given the similarity in electric motor types. The boundaries on maximum torque ( $\tau_{\text{max}}$ ) can be approximated by a second-order function:

$$\tau_{\text{max}} = \min(340, av^2 + bv + c) \quad (10)$$

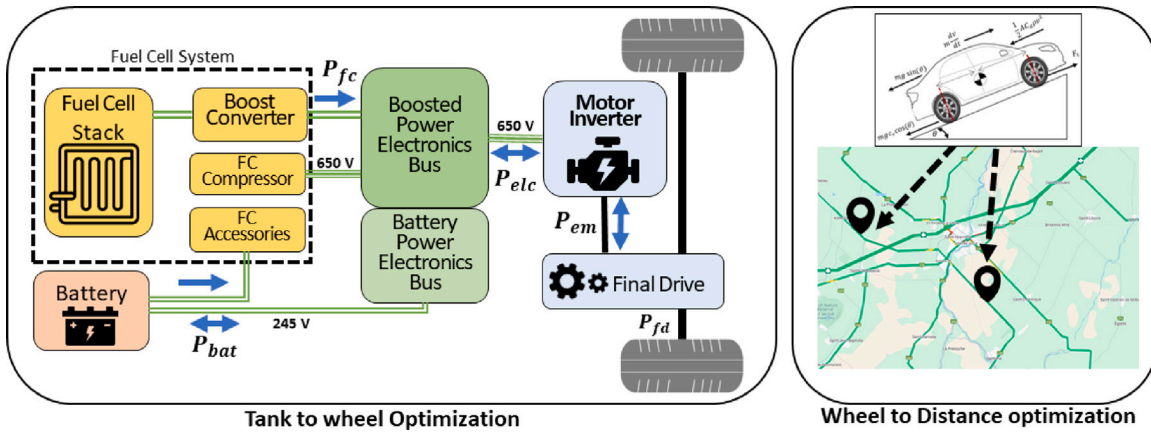


Fig. 1. Diagram of the FCEV presented in this work.

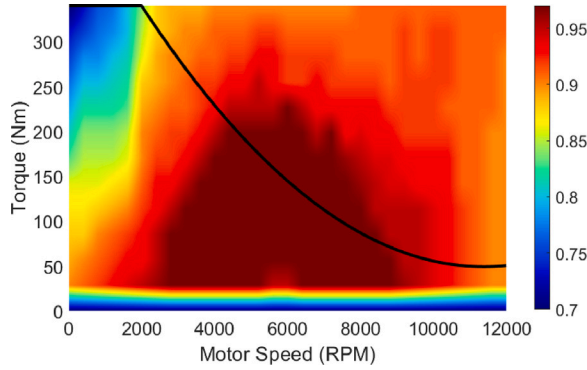


Fig. 2. Combined motor-converter efficiency map and torque-speed curve.

The electric power supplied to or generated by the motor, including its inverter is represented as  $P_{elc}$ . The efficiency of the electric motor is a function of  $\omega_{em}$  and  $\tau_{em}$  and can be calculated using a look-up table. Fig. 2 shows the efficiency map and torque-speed curve for the electric motor. The model for power flow with a combined motor-inverter can be expressed as:

$$P_m = \eta_{em}(\tau, \omega) \text{sign}(P_{elc}) P_{elc} \quad (11)$$

The overall efficiency of the powertrain can be described as  $\eta_{pt}$  and the relation between power at the wheel and electrical power at the DC link can be shown as:

$$P_{elc} = P_v \cdot \eta_{pt}^{-\text{sign}(P_v)} \quad (12)$$

In this study, the power generated by the FC,  $P_{fc}$ , and the battery,  $P_{bat}$ , are combined at the DC-link. The FC system, which includes a boost converter, is considered and will be described in more detail in the next subsection. The relationship between the hydrogen chemical power ( $P_{H_2}$ ) and the FC efficiency ( $\eta_{fc}$ ) is expressed as follows:

$$P_{fc} = P_{H_2} \eta_{fc} \quad (13)$$

resulting in the following balance in traction mode:

$$P_{elc} = P_{fc} + P_{bat} \quad (14)$$

## 2.2. Fuel cell modeling

The FC Technology Office of the US Department of Energy (DOE) identified the lack of durability and performance data for FCEVs as a significant research barrier. To address this, the Argonne National Laboratory, in collaboration with Transport Canada, conducted a technology

assessment of the 2017 Toyota Mirai. Various tests were performed using a chassis dynamometer capable of evaluating vehicles under diverse environmental conditions. The findings from these tests were detailed in [46], and the data are publicly accessible on the laboratory's website. By assuming that the FC operates under optimal conditions, utilizing an FC system efficiency map to represent the relationship between FC output electrical power and hydrogen consumption is adequate for the purpose of the presented study. Consequently, the FC system efficiency map used in this study was extracted from [46].

The FC system efficiency ( $\eta_{fc}$ ) can be expressed as a function of FC power,  $P_{fc}$ . This efficiency map accounts for all losses, including those associated with the water pump and the compressor. The hydrogen flow rate ( $\dot{m}_H$ ) can be formulated as [47]:

$$\dot{m}_{H_2} = \frac{P_{fc}(t)}{LHV_{H_2} \times \eta_{fc}} \quad (15)$$

Where  $LHV_{H_2}$  is the lower heating value of hydrogen. The efficiency value provides the equivalent hydrogen power, and by using Eq. (15), the hydrogen consumption rate can be approximated as a quadratic function of FC system power and is given as:

$$\dot{m}_{H_2} = aP_{fc}^2 + bP_{fc} + c \quad (16)$$

For validation, the output hydrogen consumption of the presented model is compared with the logged data from the experimental results. Fig. 3 illustrates the comparison between the simulated  $H_2$  flow rate and total  $H_2$  consumption and the experimentally logged data (test ID 61712044 by the Argonne National Laboratory). For test ID 61712044, the total logged hydrogen consumption is 196.84 g, while the simulated consumption is 198.9 g, corresponding to a 1 percent error in cumulative hydrogen consumption. Similarly, for test ID 61712043 and test ID 61712040, the cumulative hydrogen consumption errors were 1.5 percent and 0.7 percent, respectively, demonstrating acceptable accuracy for the FC model.

## 2.3. Battery modeling

As highlighted in the authors' previous work [45], a significant difference exists in battery capacity between BEVs and FCEVs. This distinction is critical to consider for ensuring realistic evaluations. Accordingly, the battery specifications of the 2017 Toyota Mirai are analyzed in this study. The Toyota Mirai's battery comprises 204 nickel-metal hydride cells connected in series, with each cell having a nominal voltage of 1.2 V. The total battery capacity is 1.6 kWh. The terminal voltage  $V_t$  of the battery is described by an equivalent circuit model, which includes the open-circuit voltage  $V_{oc}$ , the internal resistance  $R_b$ , and the current  $I_b$  [47]:

$$V_t = V_{oc} - I_b R_b \quad (17)$$

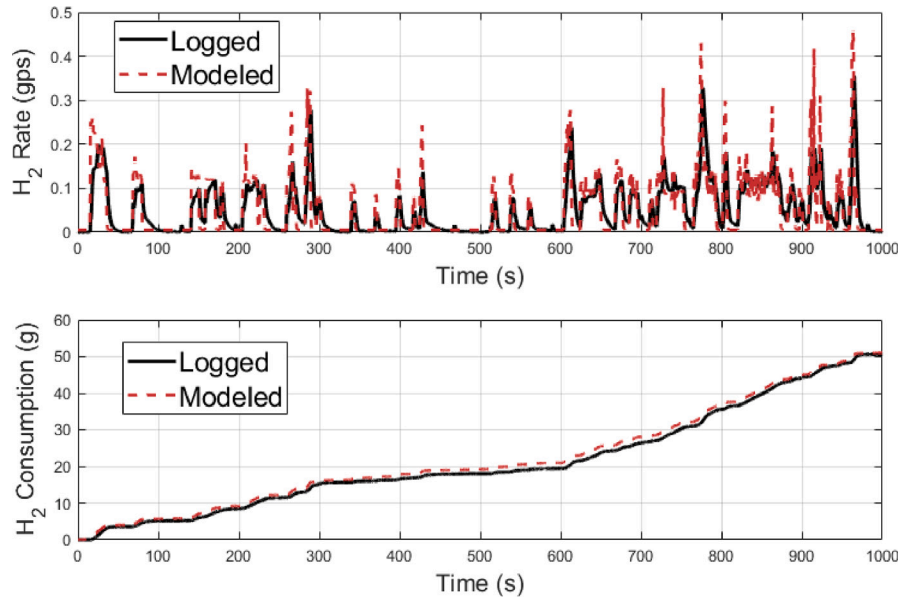


Fig. 3. Comparison of simulated and logged hydrogen flow rate (top) and total hydrogen consumption (bottom) for test ID 61712044.

$$SOC = -\frac{I_b \eta_{bat}^{sign(I_b)}}{Q_{bat}} \quad (18)$$

The open-circuit voltage is dependent on the state of charge ( $SOC$ ) of the battery and the current. The parameters used to determine  $V_{oc}$  and  $R_b$  based on the Toyota Mirai's data are discussed in [47]. The change in  $SOC$  is calculated as follows:

$$\dot{SOC} = -\frac{I_b \eta_{bat}^{sign(I_b)}}{Q_{bat}} \quad (19)$$

In this study,  $\eta_{bat}$ , representing the coulomb efficiency, is set to 0.98, and  $Q_{bat}$  denotes the battery capacity. The battery current is calculated based on the required battery power ( $P_{bat}$ ) as follows [43]:

$$I_b = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_b P_{bat}}}{2R_b} \quad (20)$$

To validate the battery model, the simulated battery behavior is compared with logged experimental data [46], using battery power as the input. Fig. 4 compares the  $SOC$  reproduced by the model with the actual measured values from test ID 61712027. The correlation between the simulated and logged  $SOC$  for test IDs 61712027, 61712053, and 61712044 is 0.9932, 0.9861, and 0.9971, respectively. These values demonstrate a strong correlation for the modeled battery. The selected datasets for the battery and FC represent well-known standardized driving cycles, including urban, highway, and mixed driving conditions. These driving cycles were chosen to ensure a comprehensive validation of the model across diverse real-world scenarios.

### 3. Optimal control methodologies

In this section, two methods for optimizing speed and energy management are introduced as optimal control problems: co-optimization, where speed planning and energy management are coupled through a single formulation, and sequential optimization, which approaches the problem in two levels. Fig. 5 shows the framework of co-optimization and sequential optimization of speed planning and EMS in the presented study.

#### 3.1. Co-optimizing speed and energy management (COP)

Driving power, FC power, and battery power can be considered for a comprehensive formulation of the problem. As suggested in [48],

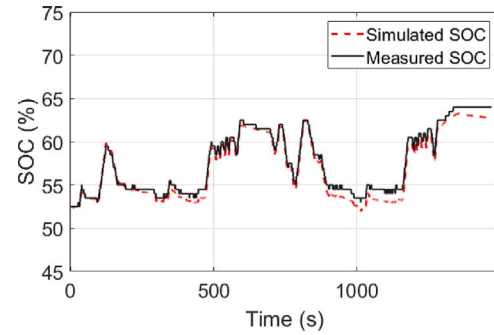


Fig. 4. Measured battery SOC from test ID 61712027 and simulated battery SOC.

to have a practical and realistic perspective, it is beneficial to use jerk values as the decision variables,  $u = [j_v, j_{bat}, j_{fc}]^T$ . The jerk values are derivatives of the associated FC, battery, and driving forces, respectively  $F_{fc}$ ,  $F_{bat}$ , and  $F_v$ . Power at the wheel, battery, and FC are associated with forces as  $P_v = F_v v$ ,  $P_{bat} = F_{bat} v$ , and  $P_{fc} = F_{fc} v$ . The equations for the derivative of forces and jerk values can be written as  $\dot{F}_v = m j_v$ ,  $\dot{F}_{bat} = m j_{bat}$ , and  $\dot{F}_{fc} = m j_{fc}$ . Considering equations (1), (16), and (19), the system dynamics ( $\frac{dx}{dt} = f(x, u, t)$ ) can be presented as:

$$\frac{d}{dt} \begin{pmatrix} s \\ v \\ m_H \\ SOC \\ F_v \\ F_{bat} \\ F_{fc} \end{pmatrix} = \begin{pmatrix} v \\ \frac{1}{m} (F_v - F_{res}) \\ aP_{fc}^2 + bP_{fc} + c \\ \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_b P_{bat}}}{2R_b Q_{bat}} \\ m j_v \\ m j_{bat} \\ m j_{fc} \end{pmatrix} \quad (21)$$

Here,  $s$  denotes the traveled distance. Other time-varying variables of the system can be directly computed using algebraic equations in terms of  $x$  and  $u$ . The problem is constrained and the inequality constraints are as follows. The maximum speed is limited by the legal speed limit:

$$0 \leq v \leq v_{max} \quad (22)$$

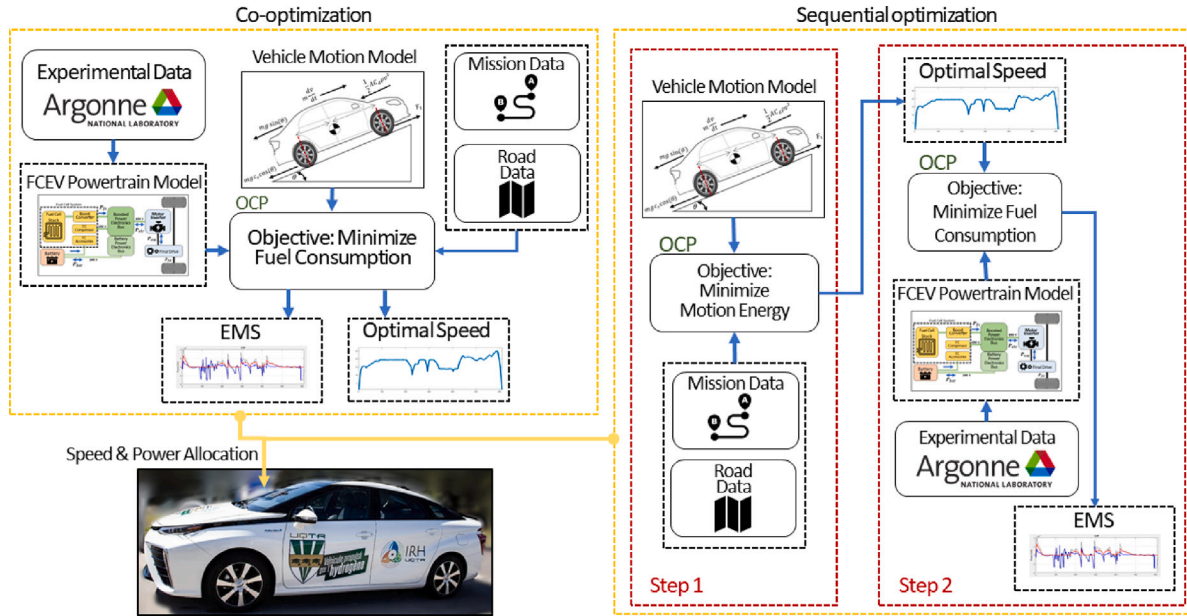


Fig. 5. The framework of co-optimization and sequential optimization of speed planning and EMS in the presented study.

To ensure driving safety and comfort, constraints are applied to both longitudinal and lateral acceleration.

$$a_{x,\min} \leq a_x \leq a_{x,\max} \quad (23a)$$

$$a_y \leq a_{y,\max} \quad (23b)$$

$a_y$  can be described as  $v^2\phi$ , where  $\phi$  is the curvature of the road center calculated from its Cartesian coordinates based on the traveled distance [49]. using (10), the maximum allowed torque limits the motor torque:

$$\tau_{\min} \leq \tau \leq \tau_{\max} \quad (24)$$

The decision variables are bounded:

$$-1 \leq j_v \leq +1 \quad (25a)$$

$$-1 \leq j_{bat} \leq +1 \quad (25b)$$

$$-1 \leq j_{fc} \leq +1 \quad (25c)$$

Other constraints are shown as:

$$SOC_{\min} \leq SOC \leq SOC_{\max} \quad (26)$$

$$0 \leq F_{fc}v \leq 114 \text{ kW} \quad (27)$$

$$-30 \text{ kW} \leq F_{bat}v \leq +30 \text{ kW} \quad (28)$$

$$F_v\eta_{pt}^{-sign(P_v)}v \leq F_{fc}v + F_{bat}v \quad (29)$$

To avoid energy losses due to applying the mechanical brakes, the power at the wheel is limited to avoid regenerative power beyond the battery's charging capacity:

$$-30 \text{ kW} \leq F_v\eta_{pt}^{-sign(P_v)}v \quad (30)$$

The objective function of the co-optimization is to minimize the total consumed hydrogen at the final time ( $T$ ) while maintaining the battery SOC within an acceptable range to avoid unrealistic reliance on the battery. It is expressed as:

$$J_{co} = \alpha \times H_2(T) + \beta \times \Sigma(SOC - 0.6)^2 \quad (31)$$

Here,  $\alpha$  and  $\beta$  are weight coefficients, and  $T$  denotes the total travel time for the consumed hydrogen. The boundary conditions for the states are:

$$s(0) = 0, \quad s(T) = l, \quad (32a)$$

$$v(0) = v(T) = 0, \quad (32b)$$

$$F_{fc}(0) = F_{fc}(T) = 0, \quad (32c)$$

$$F_{bat}(0) = F_{bat}(T) = 0, \quad (32d)$$

$$F_v(0) = F_v(T) = 0, \quad (32e)$$

$$SOC(0) = 0.60, \quad (32f)$$

$$H_2(0) = 0, \quad (32g)$$

Considering the constraints, system dynamics, and objective function the problem can be formulated as:

$$\min_{j_v, j_{fc}, j_{bat}} \quad (31)$$

s.t. :

$$(21), (22), (23), (24), (25), (26), \quad (33)$$

$$(27), (28), (29), (30), (31), (32)$$

Fig. 6 illustrates the interaction between components in the co-optimization framework. While battery power is explicitly computed in the optimization problem, when only the fuel cell has a dedicated converter, it could be handled passively in the power distribution process.

### 3.2. Sequential optimization of speed planning and energy management (SOP)

The other method to address speed planning and energy management in FCEVs is sequential optimization. In this approach, the upper layer handles the speed planning, and the calculated optimal speed is used to find the optimal power allocation between power sources. This well-established approach has been extensively examined in numerous

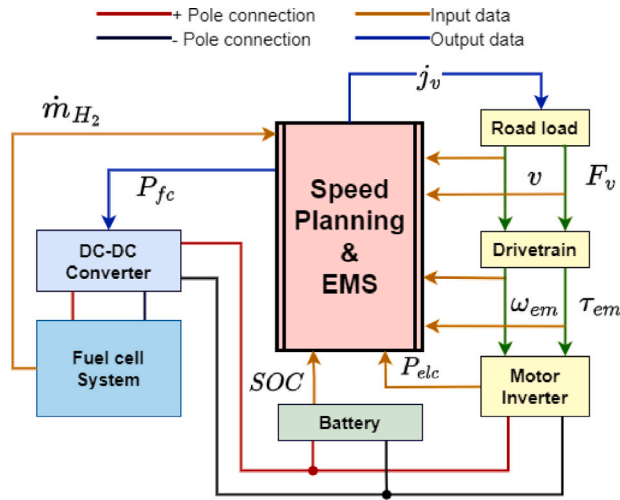


Fig. 6. The interaction between components in the co-optimization framework.

studies [3,29–32,50,51]. The system dynamics with driving jerk as a control variable ( $u = j_v$ ) can be shown as [49]:

$$\frac{d}{dt} \begin{pmatrix} s \\ v \\ F_v \end{pmatrix} = \begin{pmatrix} v \\ \frac{1}{m} (F_v - F_{res}) \\ m_v j_v \end{pmatrix} \quad (34)$$

It is worth mentioning that the separate speed planning formulation mainly remains consistent across different types of vehicles; one distinction lies in how regenerative braking is addressed in the objective function. For conventional vehicles, braking energy cannot be recovered, whereas in fully electric vehicles, all braking energy is fully recovered. In this study, the braking energy is fully recoverable, and the objective function can be formulated as follows:

$$J_{sq,1} = \int_0^T P_v dt \quad (35)$$

To complete the formulation, path constraints (22), (23a), (23b), (24), (25a), and boundary conditions (32a), (32b), and (32c) are considered. Solving (35) results in an optimal speed profile that can be used as input for the second optimization layer. The objective of the second layer is to find the optimal allocation of power between the FC and the battery that minimizes the amount of hydrogen consumption. The system dynamics for the second layer are:

$$\frac{d}{dt} \begin{pmatrix} m_H \\ SOC \\ F_{bat} \\ F_{fc} \end{pmatrix} = \begin{pmatrix} \frac{aP_{fc}^2 + bP_{fc} + c}{V_{oc} - \sqrt{V_{oc}^2 - 4R_b P_{bat}}} \\ \frac{2R_b Q_{bat}}{m j_{bat}} \\ m j_{bat} \\ m j_{fc} \end{pmatrix} \quad (36)$$

The control variables are  $u = [j_{bat}, j_{fc}]^T$  and the states for EMS layer are,  $x = [m_H, SOC, F_{bat}, F_{fc}]^T$ . The path constraints (25b), (25c), (26), (27), (28), (29) and boundary conditions (32c), (32d), (32f), and (32g) are imposed to finalize the problem. To impose (29) the optimal speed and force in the speed planning layer are used to calculate the final power demand or regenerative power at the DC link. The objective function for the energy management layer can be written as the same as the co-optimization objective function in (31).

### 3.2.1. Improved sequential optimization (ISOP)

In the previous subsection, a conventional formulation of the optimal control problem was presented. This framework does not fully account for wheel-to-distance and tank-to-wheel efficiencies. However, by incorporating additional measures, the formulation can be improved to address these factors more comprehensively. As discussed in the authors' previous work [51], while longitudinal acceleration can be

constrained with a constant value in Eq. (23a), this approach overlooks the limitations on regenerative power that the battery can absorb. Consequently, applying this constraint may result in braking power exceeding the battery's charging capacity, leading to excess energy being dissipated as mechanical power,  $P_{brake}$ . To prevent this loss, the deceleration inequality constraint can be refined by incorporating a static battery charging limit,  $P_{lim}$ . Under typical weather conditions for the Mirai, the power limit  $P_{lim}$  is 30 kW [46]. For deceleration, a new term can be introduced to impose a limit that considers the battery's capacity:

$$a_{bat} = \frac{P_{lim}}{mv\eta_{fd}\eta_{pt}} \quad (37)$$

The term  $a > a_{min}$  can be replaced by an updated constraint:

$$a > a_{bat} \quad (38)$$

When the vehicle speed falls below the minimum regenerative threshold, regenerative braking becomes inefficient, making it unnecessary to optimize for regenerative braking in this range [45]. The threshold is considered to be 2.5 m/s. As a result:

$$a_{bat} = \begin{cases} a_{min} & \text{if } v < v_{lim} \\ \max \left( a_{min}, \frac{P_{lim}}{mv\eta_{fd}\eta_{em}} \right) & \text{otherwise} \end{cases} \quad (39)$$

This constraint keeps the braking power within the battery's charging limit and avoids braking with power peaks over the mentioned limit.

### 3.3. Spatial domain formulation

The presented formulations are suitable for dealing with time-based constraints, such as speed planning for signalized intersections. They are also beneficial for scenarios where distance-based parameters, like speed limits or road grades, do not change frequently during a trip. For cases where distance-based data on the trip are subject to multiple changes, it becomes more compelling to formulate the optimal control problem in the space domain [43,52]. This approach helps to handle constraints, such as road slope, as a function of distance ( $\theta(s)$ ).

In this formulation, time ( $T$ ) is treated as one of the states, and the state variable vector can be described as  $x = [T, v, m_H, SOC, F_v, F_{fc}, F_{bat}]$ . The control variables remain the same,  $u = [j_v, j_{bat}, j_{fc}]^T$ . The system dynamics are reformulated in the distance domain; therefore, the derivatives are also taken relative to distance. The time and speed are updated as:

$$\frac{dT}{ds} = 1/v \quad (40)$$

$$\frac{dv}{ds} = \frac{1}{mv} (F_v - F_{res}) \quad (41)$$

The total fuel consumption can be calculated as:

$$H_{end} = \int_{t_0}^{t_{end}} \dot{m} dt = \int_{s_0}^{s_{end}} \dot{m} \frac{ds}{v} \quad (42)$$

The change in SOC is:

$$\frac{SOC}{ds} = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_b P_{bat}}}{2R_b Q_{bat} v} \quad (43)$$

The total energy consumed during a trip can be expressed as:

$$E = \int_{s_0}^{s_{end}} F ds \quad (44)$$

This equation corresponds to Eq. (35) when represented in the distance domain. All the inequality constraints and boundary conditions in the time domain are imposed in the distance domain with the following exceptions. To avoid division by zero, Eq. (22) can be rewritten as:

$$v_{min} \leq v \leq v_{max} \quad (45)$$

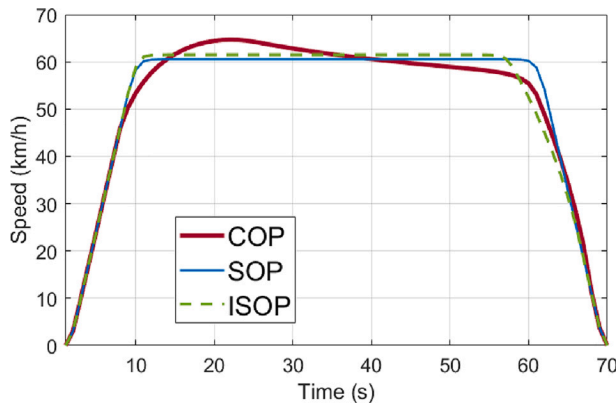


Fig. 7. Optimal speed profiles for co-optimization problem (COP), sequential optimization problem (SOP), and improved sequential optimization (ISOP).

As a result, (32c), (32d), and (32e) are not valid in the distance domain. To avoid slow speeds and excessively long final times,  $T(N+1)$  can be used in the co-optimization objective function in the distance domain:

$$J_{\text{co},s} = \alpha \times H_{2,\text{end}} + \beta \times \Sigma(\text{SOC} - 0.6)^2 + \lambda T \quad (46)$$

$\lambda$  is the weight coefficient for time. In addition, the initial time is set to zero and the trip should not exceed a maximum travel time.

$$T_0 = 0 \quad (47)$$

$$T_{\text{end}} \leq T_{\text{max}} \quad (48)$$

#### 4. Simulation and results

In this paper, the optimal control problems were formulated using the CasADi framework within MATLAB, leveraging its symbolic modeling capabilities. The IPOPT solver was employed to handle the resulting large-scale optimization problem, which is common in direct optimal control methods [53]. Non-smooth functions, such as the sign function, were approximated by smooth alternatives. This introduces a trade-off between the level of smoothness and the accuracy of the approximation [39]. The simulations were run on a computer with an Intel(R) Core(TM) i7-10700 CPU and 16 GB RAM.

##### 4.1. Case study 1, short trip

To study and compare the results of co-optimization (COP) and sequential optimal control problems (SOP and ISOP), multiple cases are considered. The first trip involves traveling 1000 m in 70 s (average speed of 51.2 km/h) on a flat road. The speed limit is assumed to be higher than the average speed. The trip starts from a stationary state (zero speed) and ends at a stationary condition. Fig. 7 shows the results of co-optimized and sequentially optimized speed profiles. The two profiles display different patterns, as the co-optimized speed profile accounts for both wheel-to-distance and tank-to-wheel efficiencies.

The SOP speed profile follows a well-known pattern: it accelerates to reach an upper-speed value for cruising, maintains that speed for most of the travel time, and then decelerates to stop. ISOP follows the same pattern during the acceleration and cruising phases, but the cruising speed is slightly higher than SOP. Deceleration begins earlier in ISOP to avoid power peaks that exceed the battery limit. In contrast, the COP speed profile, which considers powertrain dynamics, follows a different pattern. It accelerates to reach a peak speed, higher than both ISOP and SOP. Then, it starts to decelerate at a low rate for most of the remaining time, before engaging in sharper braking during the final phase of the

Table 2

Fuel consumption of COP, ISOP, and SOP.

|      | H <sub>2</sub> consumption (g) | Advantage over SOP (%) | Running time (s) |
|------|--------------------------------|------------------------|------------------|
| COP  | 3.24                           | 26                     | 1.66             |
| SOP  | 4.41                           | –                      | 0.65             |
| ISOP | 3.90                           | 11                     | 0.87             |

trip. Because battery power and SOC are explicitly considered, the COP speed profile remains within the battery's charge acceptance limits.

Fig. 8 shows the FC power, battery power, and SOC for the three methods. In COP, the FC handles the main power required during the acceleration phase, while the battery acts as a supplementary power source. When the power demand drops, the battery takes over, managing the low power demand during cruising and regenerative braking. As a result, the FC is turned off during the cruising and braking phases. ISOP and SOP exhibit similar patterns during the cruising and acceleration phases. In ISOP and SOP, unlike COP, the FC charges the battery after the acceleration power peak. As mentioned earlier, the speed profile in SOP generates regenerative power that exceeds the battery's limit. This can be observed when the battery power in SOP fails to align with the vehicle's power during the braking phase. So, although the braking torque is within the electric motor's operation region for regenerative braking, the regenerative power exceeds the battery charging limit. This means dissipation through a brake resistor or mechanical brake. This issue is resolved in ISOP.

In terms of SOC, in COP, the SOC drops consistently as the battery supports the acceleration phase and manages the power demand during the cruising phase. During the regeneration phase, the SOC increases to reach the initial value. In ISOP, the SOC drops to lower levels than in SOP, as it relies on more regenerative energy. Table 2 summarizes the hydrogen consumption and computational time for each method.

The results show that COP performs best in terms of fuel consumption, using 26 percent less hydrogen compared to SOP. However, the running time for the co-optimization framework is significantly higher than for the other methods. ISOP also demonstrates better fuel efficiency compared to SOP, with a computation time that is 33 percent longer than SOP.

It should be mentioned that the different behavior in COP emerges because it jointly optimizes both speed and energy use, unlike SOP and ISOP, which handle speed planning and power management sequentially. COP strategically shuts down the fuel cell during low-power phases, such as cruising and braking, to avoid inefficient low-load operation, relying instead on stored battery energy. This co-optimization leads to lower hydrogen consumption compared to sequential methods, where speed planning does not explicitly account for fuel cell efficiency during different driving phases.

##### 4.2. Case study 2, driving with time-dependent constraints

In certain situations, the legal speed limit may change throughout the trip, requiring the vehicle to adjust its speed accordingly. Additionally, there are cases where speed is restricted not by legal limits but by factors such as road curvature or safety considerations. These conditions require the vehicle to adhere to a speed limit at specific points along the route. In the second case study, it is assumed that the vehicle must reach specific points, A and B, on the path at designated times. Additionally, the speed at these points is limited to values below the legal speed limit. This scenario could represent a situation where a vehicle must reach an intersection at a specific time to avoid a red light and then execute a maneuver to merge into a new path. The curvature model for the path imposes additional speed constraints on the problem. In this case, the vehicle must travel 1000 m in 65 s (point A) and 2100 m in 130 s (point B), with speed limits at points A and B

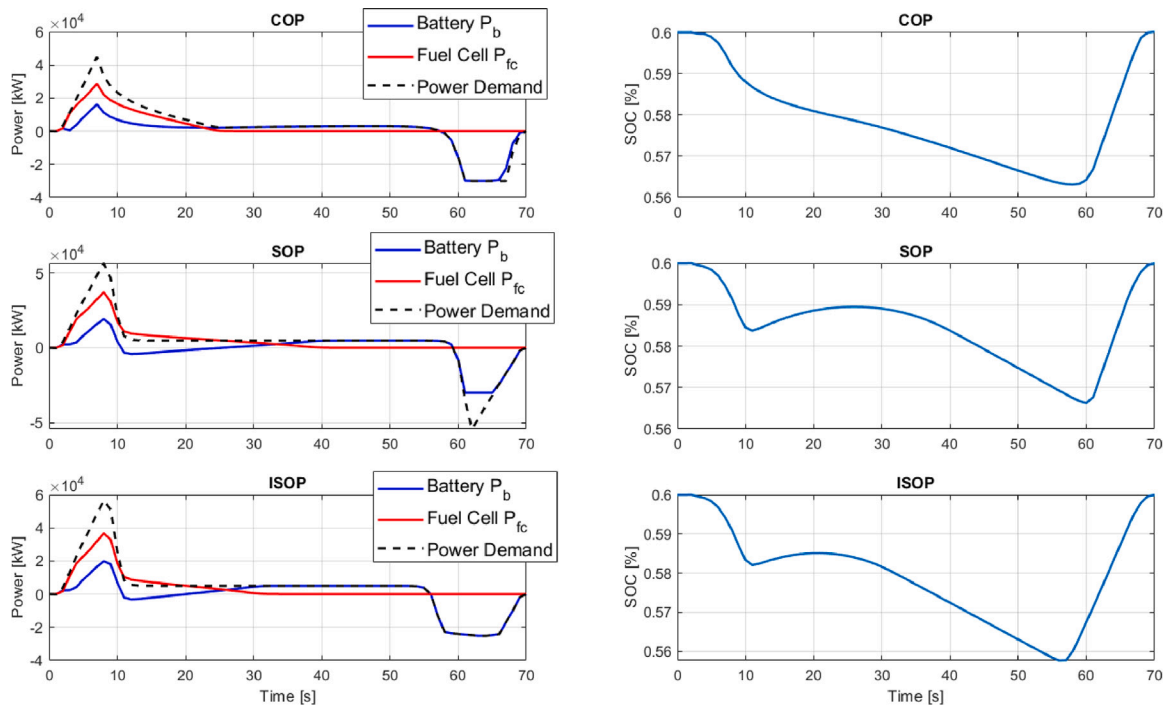


Fig. 8. Optimal power allocation for co-optimization problem (COP), sequential optimization problem (SOP), and improved sequential optimization (ISOP).

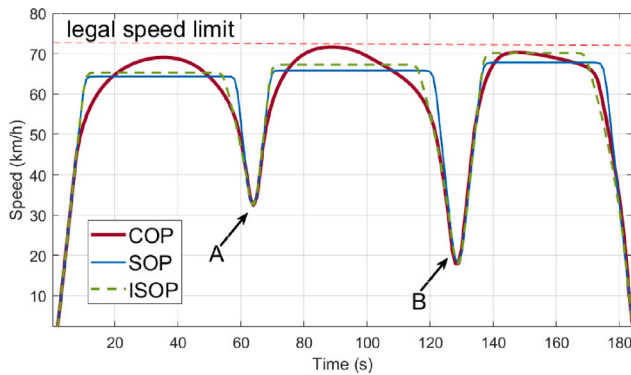


Fig. 9. Case study 2: Optimal speed profiles for COP, SOP, and ISOP.

of 32 km/h and 18 km/h, respectively. The overall mission is to travel 3 km in 180 s.

The speed profiles are depicted in Fig. 9. COP exhibits its characteristic pattern, with a gradual acceleration to a high-speed peak, followed by a soft deceleration phase, and finally braking. The cruising speed for SOP and ISOP is lower, following the same pattern as observed in the previous study.

Power allocations for the FC and battery, as well as SOC in case study 2, are shown in Fig. 10. In COP, during the first acceleration phase, power allocation is similar to the first case study. In the second acceleration phase, since the SOC is high, the battery plays a larger role in providing the power demand. In the third acceleration phase, with high SOC and the upcoming final regenerative brake, the battery takes the lead in providing traction force. In the final phase and braking, the SOC increases to 60%. In SOP, the power allocation nearly follows the same pattern during the trip for each acceleration and deceleration phase, depending more on the battery as the SOC increases. ISOP shows the same behavior, and the same as the previous case, the regenerative power is within the battery's charging limit. SOP consumed 15.22 g of hydrogen, while COP and ISOP demonstrated improvements of 25% and 11% in fuel efficiency, respectively.

It should be highlighted that to ensure a consistent evaluation of hydrogen consumption and prevent the conversion of SOC fluctuations into equivalent hydrogen consumption, a charge-sustaining strategy was enforced in the optimization. A penalty term in the cost function enforces SOC stability by minimizing deviations from a reference level. A sufficiently large weight factor ensures SOC returns to its initial value, maintaining charge balance across all case studies.

#### 4.3. Case study 3, long route

This subsection evaluates the effectiveness and robustness of the proposed methods using a more realistic scenario. The vehicle mission involves a 10.09 km rural route in Quebec, as depicted in Fig. 11.

The road geometry is extracted from Google Maps and converted into the curvature model. In addition, the road is also extracted and considered as  $\theta(s)$ . The curvature model is then used to set a variable upper speed limit at specific points along the path to reflect real conditions where the speed limit is below the legal speed limit. Markers 1, 2, and 3 in Fig. 11 indicate these points. Traffic conditions are not considered, meaning the vehicle's speed is unaffected by other vehicles. For consistency in comparison, the travel duration is limited to no longer than 610 s. Fig. 12 shows the speed profiles over the traveled distance and road grade of the rural path.

After introducing realistic road slopes, COP results in a speed profile that changes more frequently to handle power fluctuations caused by slope variations. For the majority of the trip, the vehicle speed remains close to the maximum legal speed. In contrast, for SOP and ISOP, since the powertrain is not directly involved in speed planning, the introduction of varying road slopes does not affect the flat pattern of their speed profiles. Additionally, the speed profiles for SOP and ISOP remain well below the speed limit in the final segment of the trip.

The battery power, FC power, and state of charge are illustrated in Fig. 13. Introducing the road slope adds more challenges for traction power. As observed, COP maintains low traction power to prevent pushing the FC to operate at less efficient points, whereas in ISOP and SOP, traction power peaks at higher values. In the final stages of the mission, when the power demand decreases, the battery takes the lead in meeting the power request.

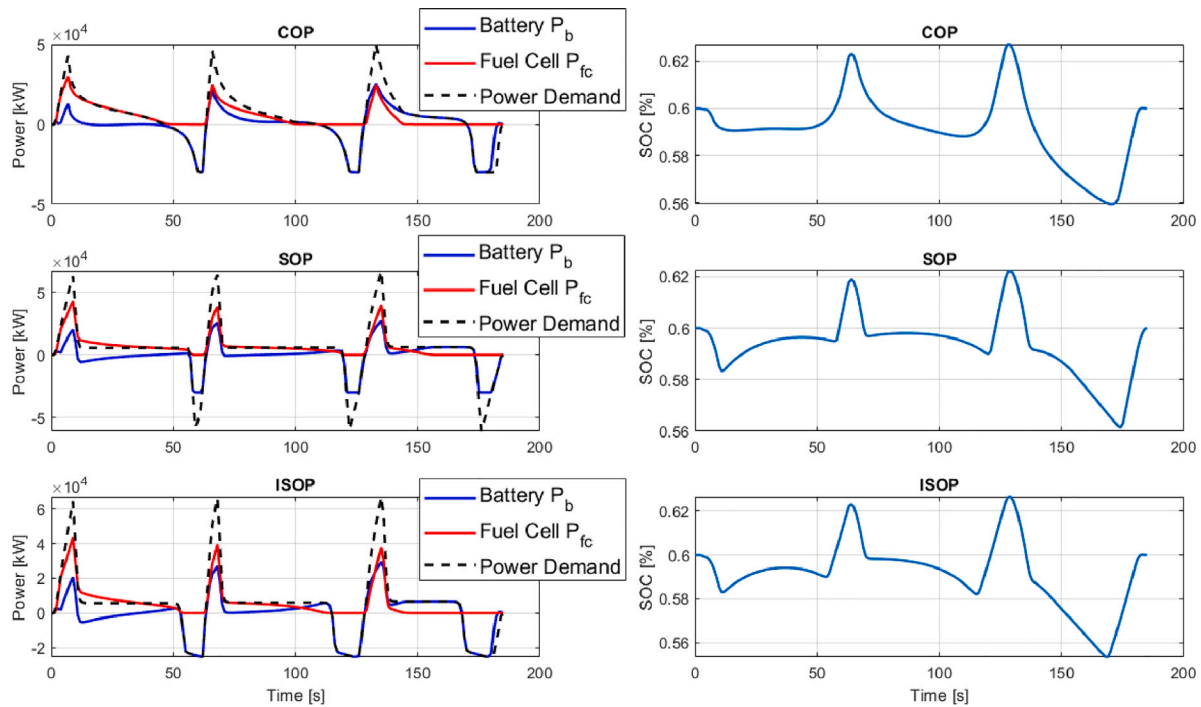


Fig. 10. FC power, battery power, and SOC comparison for COP, SOP, and ISOP in case study 2.

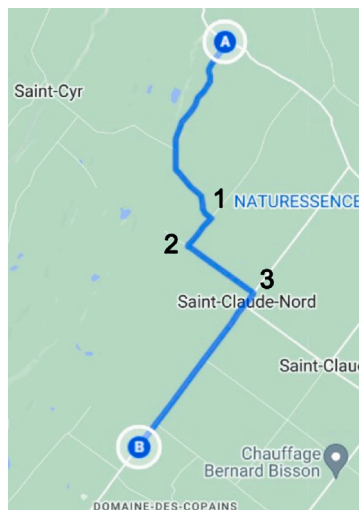


Fig. 11. The selected path for case study 3 in a rural area in Quebec.

**Table 3**  
Fuel consumption and computation effort for driving on 10.9 km rural road.

|      | H <sub>2</sub> consumption (g) | Advantage over SOP (%) | Running time (s) |
|------|--------------------------------|------------------------|------------------|
| COP  | 24.69                          | 36                     | 446              |
| SOP  | 39.01                          | –                      | 73               |
| ISOP | 35.92                          | 7                      | 162              |

Table 3 shows the fuel efficiency and computation effort for COP, SOP, and ISOP.

The computation time in COP is considerably longer than in sequential methods. However, the results in this case study demonstrate that in realistic driving scenarios, which include road slopes and multiple speed limit changes, the advantage of COP over SOP and ISOP is more significant, with fuel savings of up to 36%. Although ISOP

performed competitively with COP on flat roads while requiring less computational effort, its fuel-saving advantage diminishes in more realistic setups, and its computational time exceeds that of SOP. This aligns with findings reported in [43], which highlight the benefits of co-optimization methods for bumpy roads.

In the final deceleration phase before coming to a full stop, In all methods, EMS does not use all the available power to charge the battery in order to maintain the final SOC. This means the regenerative power is not directed to the battery, and the stopping power can be provided as a mechanical braking force,  $P_{brake}$ , or regenerated power is dissipated.

In realistic driving conditions with variable slopes and speed limits, COP adapts the powertrain's energy use dynamically, allowing it to respond more efficiently to fluctuations in power demand. It also dynamically modifies the vehicle's speed profile to accommodate changing power demands without unnecessary fuel consumption peaks. In contrast, SOP and ISOP are less responsive to such variations. When encountering a slope, for instance, they do not adjust acceleration and power allocation proactively, leading to higher hydrogen consumption.

A significant difference is observed when comparing the proposed method with studies that focus solely on the EMS layer without optimizing the speed profile [12,15,18–20], as well as with sequential optimization approaches that separately optimize speed planning and EMS [29,30,32,33,35]. While the vehicle follows the same route and mission, the requested power can vary substantially depending on the speed profile. EMS-only strategies lack direct speed optimization, leading to power fluctuations dictated by predefined or reactive speed control. Similarly, in sequential optimization, even though speed planning is considered in an upper layer, the EMS must still handle unnecessary power peaks due to the lack of simultaneous coordination. In Fig. 13, the proposed integrated approach results in peak power demands as low as 40 kW, whereas the sequential method can generate peak power requirements approaching 100 kW to finish the same mission. This highlights a key limitation of these approaches: despite efforts to forecast or plan speed in a separate layer, the EMS remains burdened with abrupt power variations, reducing overall system efficiency. By optimizing speed and energy management simultaneously, the proposed method effectively mitigates these peaks, leading to a smoother power profile and improved energy efficiency.

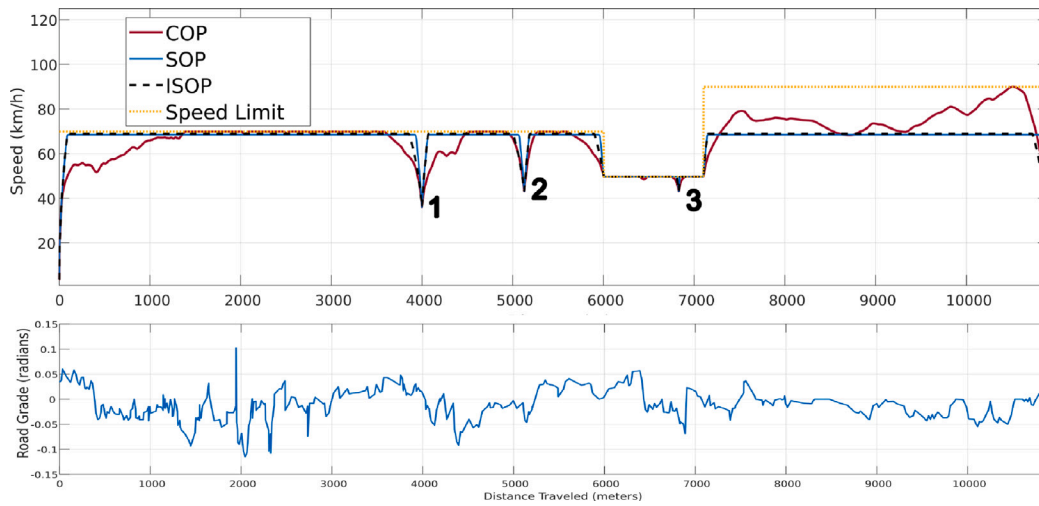


Fig. 12. COP, SOP, and ISOP speed profiles over a 10.9 km route and the road grade.

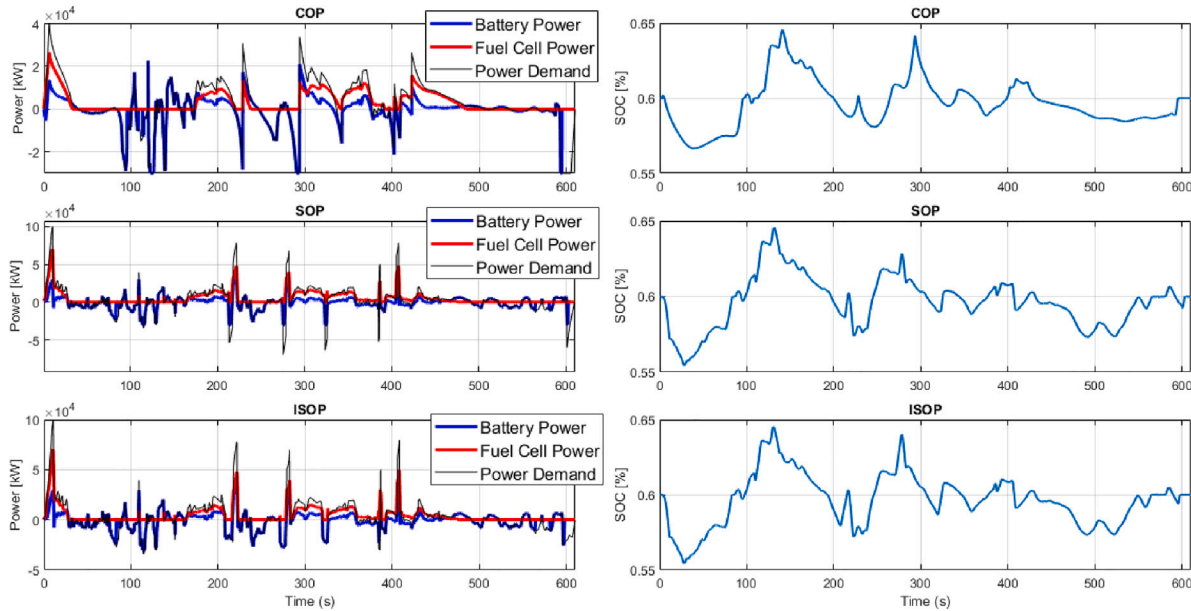


Fig. 13. FC power, battery power and SOC plots for COP, SOP, and ISOP for a 10.9 km route.

It should be noted that if the vehicle were equipped with a larger battery pack comparable to that of PHEVs, as energy density is independent of battery size, a larger and heavier battery pack can decrease overall efficiency, as the additional weight increases the energy required to propel the vehicle and its components [54]. However, increasing the battery's charge acceptance limit can modify the driving profile, as the vehicle can rely more on regenerative braking to recover energy efficiently.

## 5. Conclusion

This study investigates an optimal control problem for speed planning and energy management in an FCEV, comparing co-optimization (COP) with sequential optimization (SOP and ISOP). The proposed COP framework integrates traveled distance, speed, driving force, battery SOC, and hydrogen consumption into a unified optimization problem to determine the optimal speed and power allocation.

The performance of COP, SOP, and ISOP was evaluated in different driving scenarios, highlighting key improvements in fuel efficiency and computational effort, as summarized below:

- Fuel consumption on flat roads: In a 1000 m trip completed in 70 s, COP reduced fuel consumption by 25 percent compared to SOP, while ISOP achieved an 11 percent reduction over SOP.
- Fuel consumption on realistic routes with slopes and speed variations: On a 10.09 km rural route with road slopes and speed limit variations, COP achieved a 36 percent reduction in fuel consumption compared to SOP. ISOP's advantage decreased in these conditions, providing only a 7 percent improvement over SOP.
- Computation time comparison: SOP has the shortest runtime, followed by ISOP (33 percent longer than SOP), while COP requires more than twice the time of SOP. For a 1000 m look-ahead window, the computation times are 0.65 s for SOP, 0.87 s for ISOP, and 1.66 s for COP.

The current study provides an offline reference speed profile and energy management strategy for any given route or trip scenario. By incorporating a short look-ahead window, the method could be adapted for online applications. It can also generate reference speed and power allocation profiles based on road conditions, helping FCEVs plan energy

use more efficiently based on upcoming road grades, speed limits, and braking opportunities.

The proposed method is computationally demanding, making it unsuitable for all types of real-time applications, particularly those requiring high-speed decision-making in rapidly changing environments. As a result, improving real-time feasibility and addressing dynamic traffic conditions will be the primary focus of future work. Additionally, future efforts will extend to cover issues related to FC degradation.

The results demonstrate that optimizing power allocation in an FCEV can significantly reduce hydrogen consumption by prioritizing battery support during low-power phases and strategically managing fuel cell operation to avoid inefficient low-load conditions. This suggests that future FC systems should optimize cold-start performance and improve transient load response to better integrate with predictive energy management strategies. Enhancing fuel cell efficiency during low-power phases and ensuring smooth transitions between different load levels would further improve system energy savings and durability.

### CRedit authorship contribution statement

**Seyed Mohammad Hosseini:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sousso Kelouwani:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization. **Mohsen Kandidayeni:** Writing – review & editing, Validation, Methodology, Data curation. **Ali Amammou:** Writing – review & editing, Formal analysis, Conceptualization. **Mehdi Soleymani:** Writing – review & editing, Visualization.

### Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to assist with grammar checking. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Seyed Mohammad Hosseini reports financial support was provided by Natural Science and Engineering Research Council of Canada and the Canada Research Chair Program. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### 3.5 Concluding Remarks

This chapter focused on improving the energy efficiency of fuel cell hybrid electric vehicles through optimization of speed planning and EMS. Two strategies were investigated: an enhanced sequential method and a fully integrated co-optimization framework.

The first article addressed a critical shortcoming in conventional sequential optimization. By introducing a dynamic deceleration constraint based on regenerative power limits, it made the speed planning layer more aware of powertrain constraints. This lightweight adjustment led to measurable improvements in energy recovery and fuel efficiency, demonstrating that even partial integration of system limitations can improve results within a sequential setup. It also showed that shifting key powertrain constraints forward into the speed optimization phase can significantly enhance energy efficiency, even within a sequential optimization framework. This contribution serves as an important stepping stone toward more advanced co-optimization approaches.

The second article extended this idea further by removing the separation between speed planning and energy management entirely. Through co-optimization, the vehicle's speed profile and power distribution were optimized simultaneously. The results showed significant gains in fuel economy and smoother control behavior compared to the sequential method. This confirms the importance of considering vehicle motion and energy flow in a unified framework, particularly for intelligent and connected vehicle applications. This article represents a core contribution of the thesis. It brings together earlier insights on braking constraints and lays the groundwork for future developments, such as online MPC and adaptive optimization methods. The next chapters build on this work to explore how the proposed co-optimization can be adapted for real-time driving

scenarios.

Together, the two articles in this chapter demonstrate a clear evolution: from improving the realism of sequential methods to developing a more complete, system-aware optimization strategy. The findings also highlight the trade-offs between complexity and performance, a theme that carries forward to the next chapters, where the focus shifts toward online implementation and real-time control.

It demonstrated that incorporating regenerative power constraints directly into the speed planning layer improves overall system performance. By introducing a dynamic deceleration limit based on the actual regenerative capacity of the vehicle's battery and power electronics, the optimized speed profile remains within energy absorption limits, reduces fuel consumption, and prevents unnecessary energy dissipation.

## Chapter 4 - Online Integrated Optimization of Speed and Energy

### Management on Slippery Roads

#### 4.1 Introduction

In this chapter, the study is extended to introduce an integrated framework for online applications. In the previous chapter, an offline integrated method was introduced, but the approach was not well-suited for real-time driving and handling unexpected changes along the route. Here, the integrated approach is reformulated as a nonlinear model predictive control (NMPC). The NMPC is called at each 0.1s interval and generates the optimal speed and power allocation for a horizon of 50 m.

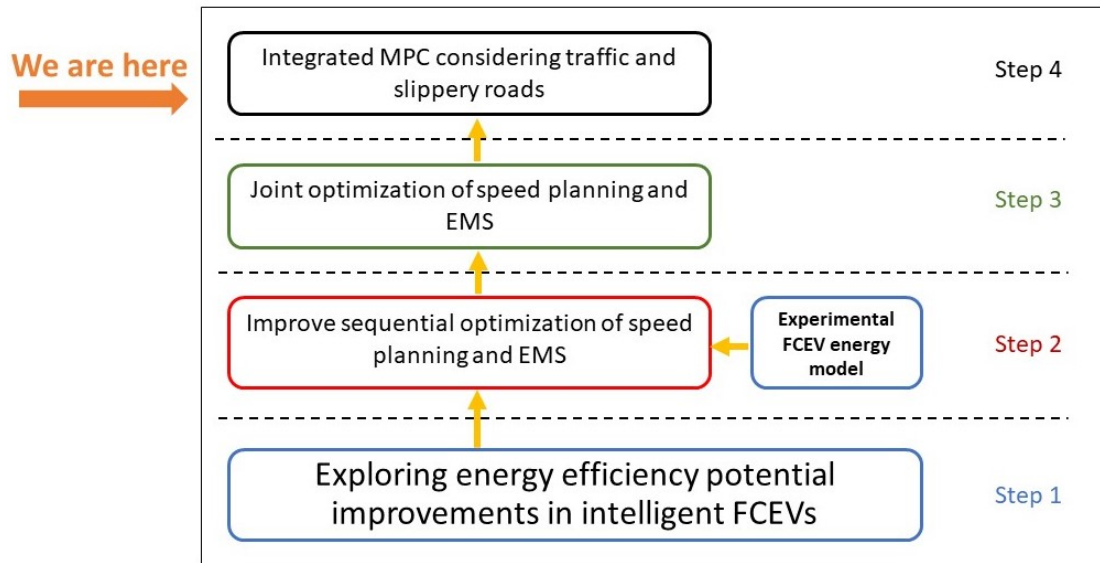


Figure 4.1 The last step in the development of the study guided by research objectives

In addition, to investigate the impact of more extreme and real-world situations, the slippery road surface on hilly and winding routes is studied. The combined effect of road curvature, road slope, and the road adhesion coefficient is considered to provide safe and

energy-efficient speed profiles.

Moreover, a safe car-following strategy is introduced to extend the applicability of the framework to traffic scenarios. Unlike the offline approach in the previous chapter, which considered only free-driving conditions, the nonlinear model predictive control (NMPC) formulation here accounts for interactions with a lead vehicle. A long short-term memory (LSTM) network predicts the lead vehicle's speed over the prediction horizon, while a friction-adaptive time headway policy dynamically adjusts the safe following distance based on the estimated road adhesion coefficient. This allows the vehicle to maintain both safety and efficiency when following another vehicle, especially under slippery winter conditions where braking distances increase significantly.

By integrating these features, the proposed online co-optimization framework offers a unified strategy that balances fuel efficiency, safety, and comfort. It is designed for real-time implementation and validated through hardware-in-the-loop experiments, showing its capability to handle both challenging road surfaces and realistic traffic interactions.

#### **4.2 Article 4: Integrated Co-Optimization of Speed Planning and Energy Management for Fuel Cell Hybrid Electric Vehicles Under Slippery Road Conditions (submitted)**

# Integrated Co-Optimization of Speed Planning and Energy Management for Fuel Cell Hybrid Electric Vehicles under Slippery Road Conditions

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**Abstract**—Integrated optimization of speed planning and energy management (EMS) in fuel cell hybrid electric vehicles (FCHEVs) enables more energy-efficient driving compared with sequential methods or approaches focused only on EMS optimization. These benefits become even more significant in the context of intelligent and connected driving. However, integrated methods face high computational demands, and prior studies have largely neglected the effects of hilly terrain, low road adhesion, and winter conditions. This study addresses these gaps by incorporating road slope, curvature, and adhesion coefficient as safety constraints in a co-optimization framework based on nonlinear model predictive control (COP-NMPC). Results highlight the impact of slippery surfaces, with hydrogen consumption dropping by up to 33% on snowy and icy roads. Slippery conditions are further considered by adapting the safe gap to the lead vehicle. Compared to a full-preview offline benchmark, COP-NMPC consumed 11.5% and 12.5% more fuel across two routes. However, hardware-in-the-loop (HIL) tests demonstrated real-time feasibility, with a median solving time of 26 ms, ensuring safe and efficient operation.

**Index Terms**—Co-optimization, Fuel cell hybrid electric vehicle, Energy management strategy, Speed planning, Model predictive control.

## I. INTRODUCTION

IN recent years, carbon-neutral and zero-emission policies have been promoted in the transportation industry [1]. Fuel cell hybrid electric vehicles (FCHEVs) are among the clean transport options that produce zero emissions [2].

The combination of intelligent driving and FCHEVs presents new opportunities to improve fuel efficiency through coordinated speed planning and energy management. Employing energy-efficient speed trajectories and optimizing the energy management strategy (EMS) both help minimize fuel consumption in FCHEVs. Each approach, however, poses its own challenges. Speed planning must account for vehicle dynamics, road conditions (such as slopes and speed limits), and traffic data to determine the optimal speed profile, while

EMS must address the complexity of a nonlinear powertrain with multiple power sources [3]. Although addressing these two problems separately remains common in research and industry, with numerous studies focusing solely on speed optimization for eco-driving [4], [5] and others dedicated to developing advanced EMS strategies for power split control [6], [7], a growing body of work is exploring the benefits of integrating them to achieve greater efficiency.

This can be approached from two directions. The first is to decouple the subproblems of speed planning and EMS into a sequential optimization, where the first layer determines the speed profile and the second layer solves the EMS optimization based on this outcome. Wei et al. In [8], a sequential optimization scheme was used to handle speed planning, energy management, and energy recovery for an FCHEV in dynamic urban traffic. This concept was later expanded in [9] to incorporate dynamic cornering scenarios. Meshginqalam et al. [10] developed a convex bi-level optimization method for FCHEVs that accounted for powertrain losses. In [11], a control framework with a multi-objective EMS was introduced for FCHEVs.

The sequential approach is commonly used for complex driving scenarios but, as shown in the authors' previous work [12], it can be up to 30% less efficient than an integrated method. The integrated approach solves speed planning and EMS jointly in a unified co-optimization framework, though its main limitation for online use is high computational demand, which often leads to simplifications. Chen et al. [13] studied a series HEV case, comparing simultaneous and hierarchical control and showing better results for the integrated formulation. Li et al. [14] proposed a data-driven solution for PHEVs combining eco-driving with EMS optimization. Kim et al. [15] compared sequential and co-optimization for FCHEVs using dynamic programming and confirmed the superior performance of the latter, though with major simplifications. Liu et al. [16] proposed a two-step spatial-domain eco-driving method considering only speed limits and road slope. More recent works [17]–[19] applied reinforcement learning for integrated eco-driving and EMS but remained limited to flat, simplified roads.

Most integrated and sequential methods assume flat, straight roads and normal weather, unlike real conditions in regions such as Quebec, where roads are often hilly, winding, and snow- or ice-covered. Heuts et al. [20] extended Eco-Driving for BEVs by adding curvature-aware cornering and a slip con-

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This work has not been presented at a conference previously.

TABLE I  
COMPARISON BETWEEN THE PRESENTED WORK AND RELATED STUDIES

| Ref.             | Veh.         | Integr. | Real-time | Slope | Traffic | Slippery road |
|------------------|--------------|---------|-----------|-------|---------|---------------|
| [21]             | PHEV         | ✓       | ✗         | ✗     | ✓       | ○             |
| [16]             | FCHEV        | ✓       | ✗         | ✓     | ✗       | ✗             |
| [20]             | BEV          | ✓       | ○         | ✓     | ✗       | ○             |
| [22]             | HEV          | ✓       | ✓         | ✗     | ✗       | ✗             |
| [17]             | FCHEV        | ✓       | ○         | ✗     | ✓       | ✗             |
| [15]             | FCHEV        | ✓       | ✗         | ✓     | ✗       | ✗             |
| [10]             | FCHEV        | ✗       | ✓         | ✓     | ✗       | ✗             |
| [23]             | SHEV         | ✓       | ✗         | ✓     | ✗       | ✗             |
| [24]             | FCHEV        | ✗       | ✓         | ✗     | ✗       | ✓             |
| [25]             | HEV          | ✓       | ✓         | ✓     | ✓       | ✗             |
| [26]             | FCHEV        | ✗       | ✓         | ✗     | ✓       | ✗             |
| <b>This work</b> | <b>FCHEV</b> | ✓       | ✓         | ✓     | ✓       | ✓             |

✓=Implemented, ✗=Not, ○=Partial.

straint, estimating curvature from GPS using the osculating-circles method and formulating dynamics in the spatial domain, achieving up to 25% energy savings but neglecting traffic and slope. Ma et al. [21] proposed a co-optimization framework for connected PHEVs on slippery roads with a variable time headway, jointly optimizing acceleration, powertrain mode, and energy split, though assuming a flat, straight road without real-time evaluation. A summary of related works is provided in Table I. From previous studies on speed and EMS optimization, three gaps emerge. First, few works address real-time co-optimization of speed and EMS in FCHEVs. Although integrated methods exist [15]–[17], they are not suitable for online use. Second, road slope is often neglected, despite its influence on power demand and the friction circle on slippery roads. Third, safe driving under winter and low-adhesion conditions remains underexplored. While [20], [21] discuss this topic, the combined effects of slope, adhesion, and curvature, as well as car-following on slippery roads, are still missing.

This paper develops an online integrated co-optimization framework for autonomous FCHEVs under winter road conditions to address the identified research gaps. The framework unifies speed planning and energy management in a spatial-domain NMPC structure, incorporating detailed vehicle and road models that account for slope, curvature, and traction variations. It also introduces a friction-adaptive car-following strategy to ensure safe interactions with lead vehicles on slippery roads. Finally, the approach is formulated for real-time implementation and validated through hardware-in-the-loop testing. This work extends the authors' previous study [12] and contributes to fuel efficiency and driving safety in autonomous FCHEV research under winter conditions in the following ways:

- 1) Developed an online integrated co-optimization framework for simultaneous speed planning and energy management in FCHEVs, incorporating adhesion coefficient, slope, and curvature to generate energy-efficient and safe speed profiles on slippery roads.
- 2) Designed a friction-adaptive car-following strategy that predicts lead-vehicle motion and adjusts following distance based on road adhesion, ensuring safety under

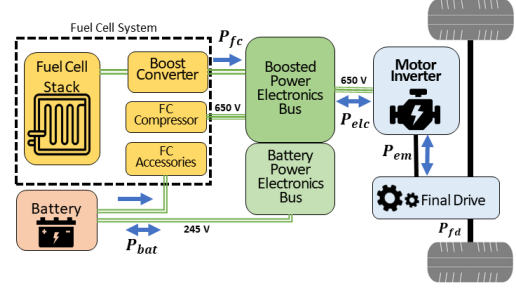


Fig. 1. Architecture Toyota Mirai presented in this work [12]

TABLE II  
MAIN VEHICLE PARAMETERS [10], [27].

| Symbol        | Description               | Value               |
|---------------|---------------------------|---------------------|
| $m$           | Vehicle mass              | 1940 kg             |
| $C_{rr}$      | Rolling-resistance coeff. | 0.008               |
| $C_D$         | Drag coefficient          | 0.29                |
| $A$           | Frontal area              | 2.38 m <sup>2</sup> |
| $r_{wh}$      | Wheel radius              | 0.371 m             |
| $fd$          | Final-drive ratio         | 3.478               |
| $P_{fc,max}$  | Max fuel-cell power       | 114 kW              |
| $P_{bat,max}$ | Max battery power         | 30 kW               |
| $Q_{bat}$     | Battery capacity          | 6 Ah                |
| $\eta_{fd}$   | Final-drive efficiency    | 0.97                |
| $\tau_{max}$  | Max motor torque          | 340 N·m             |

varying traction.

- 3) Implemented a spatial-domain NMPC for real-time operation, validated through high-fidelity simulations and HIL tests, achieving near-benchmark performance within real-time limits.
- 4) Conducted a quantitative analysis of road adhesion effects, proposing a friction-aware approach that prevents overestimation of safe speeds and improves winter driving efficiency.

The paper is organized as follows: Section II presents the vehicle and powertrain models; Section III details the proposed COP-NMPC framework and slippery-road approach; Section IV discusses results and performance; and Section V concludes the study and outlines future work.

## II. MODEL DESCRIPTION

An intelligent FCHEV representative of a Level-3 autonomous light-duty vehicle is used in this study. In Level-3 automation, the system drives within mapped environments while the driver remains ready to intervene [1]. The vehicle employs a fuel cell as the main power source and a battery as the secondary one (Fig. 1). Its powertrain and parameters are based on the 2017 Toyota Mirai, used here as the reference platform [27]. Key specifications are listed in Table II.

### A. Vehicle dynamics

The longitudinal dynamics are:

$$m \frac{dv}{dt} = F_v - F_{brk} - F_{res} \quad (1)$$

where  $m$  is the vehicle mass,  $F_v$  is the longitudinal wheel force (positive in traction, negative in braking),  $F_{brk}$  is the brake

force ( $F_{\text{brk}} \geq 0$ ), and  $F_{\text{res}}$  is the total resistance, modeled as [28]:

$$F_{\text{res}} = 0.5\rho_a A C_D v^2 + mg \cos(\theta) C_{\text{rr}} + mg \sin(\theta) \quad (2)$$

Here,  $C_{\text{rr}}$  represents the rolling-resistance coefficient,  $A$  is the frontal area,  $C_D$  is the drag coefficient,  $\rho_a$  is the air density ( $1.225 \text{ kg/m}^3$ ),  $g$  is the gravitational acceleration ( $9.81 \text{ m/s}^2$ ),  $\theta$  is the road grade (rad), and  $v$  is the vehicle speed (m/s). The mechanical power at the wheels is:

$$P_v = F_v v \quad (3)$$

In traction, the wheel power equals the final-drive output ( $P_v = P_{\text{fd}}$ ). In pure regenerative braking (no mechanical brakes), the same equality holds during braking. When mechanical braking power  $P_{\text{brk}}$  ( $P_{\text{brk}} = -F_{\text{brk}} v$ ) is present:

$$P_{\text{fd}} = P_v - P_{\text{brk}} \quad (\forall P_v < 0) \quad (4)$$

The mechanical brake is treated as a power loss (negative by convention). This study does not model front/rear brake-force distribution, and regenerative power is assumed not to be constrained by axle split.

The bidirectional link between the electric motor's mechanical power,  $P_m$ , and the final-drive output is modeled as:

$$P_{\text{fd}} = \eta_{\text{fd}}^{\text{sign}(P_m)} P_m \quad (5)$$

with the motor's mechanical power given by:

$$P_m = \tau_{\text{em}} \omega_{\text{em}} \quad (6)$$

Assuming constant final-drive efficiency  $\eta_{\text{fd}}$ , with  $\tau_{\text{em}}$  as the load torque and  $\omega_{\text{em}}$  as the electric motor's rotational speed, the relation between motor and wheel speeds can be described as:

$$\omega_{\text{em}} = \frac{v \cdot fd}{r_{\text{wh}}} \quad (7)$$

$$\omega_{\text{wheel}} = \frac{\omega_{\text{em}}}{fd} \quad (8)$$

where  $fd$  is the final-drive ratio and  $r_{\text{wh}}$  is the wheel radius. The relation between  $F_v$  and  $\tau_{\text{em}}$  is:

$$F_v = \frac{\tau_{\text{em}} fd \eta_{\text{fd}}^{\text{sign}(\tau_{\text{em}})}}{r_{\text{wh}}} \quad (9)$$

### B. Electric motor (EM)

Considering EM physical limits is crucial since maximum torque constrains both acceleration and regeneration. For FCHEVs like the Toyota Mirai, detailed EM data are unavailable; hence, following [10], a scaled Toyota Prius motor map is used as a proxy. The maximum torque limit is approximated by a quadratic:

$$\tau_{\text{max}} = \min(340, av^2 + bv + c) \quad (10)$$

The electric power at the motor terminals (including the inverter) is denoted  $P_{\text{elc}}$ . The EM efficiency depends on  $\omega_{\text{em}}$  and  $\tau_{\text{em}}$  and is obtained from a lookup table. The combined motor-inverter power-flow model is:

$$P_m = \eta_{\text{em}}(\tau_{\text{em}}, \omega_{\text{em}})^{\text{sign}(P_{\text{elc}})} P_{\text{elc}} \quad (11)$$

### C. Source-to-wheel power mapping

Let  $\eta_{\text{pt}}$  denote the overall powertrain efficiency; the relation between wheel power and DC-link electrical power is:

$$P_{\text{elc}} = P_v \eta_{\text{pt}}^{-\text{sign}(P_v)} \quad (12)$$

In this study, the fuel cell and battery powers,  $P_{\text{fc}}$  and  $P_{\text{bat}}$ , are combined at the DC link. The fuel cell system employs a boost converter, described in the next subsection. The relation between hydrogen chemical power  $P_{\text{H}_2}$  and fuel cell efficiency  $\eta_{\text{fc}}$  is:

$$P_{\text{fc}} = P_{\text{H}_2} \eta_{\text{fc}} \quad (13)$$

resulting in the following balance in traction mode:

$$P_{\text{elc}} = P_{\text{fc}} + P_{\text{bat}} \quad (14)$$

### D. Fuel cell

The 2017 Toyota Mirai fuel cell efficiency map from [27], based on Argonne National Laboratory chassis-dynamometer tests, is used to relate electrical power to hydrogen consumption under near-optimal operation. The fuel cell efficiency  $\eta_{\text{fc}}$ , modeled as a function of power  $P_{\text{fc}}$ , includes auxiliary losses such as the pump and compressor. The hydrogen mass-flow rate is given by [29]:

$$\dot{m}_{\text{H}_2} = \frac{P_{\text{fc}}(t)}{LHV_{\text{H}_2} \eta_{\text{fc}}} \quad (15)$$

where  $LHV_{\text{H}_2}$  is the lower heating value of hydrogen. Using Equation (15), hydrogen consumption is approximated quadratically:

$$\dot{m}_{\text{H}_2} = a P_{\text{fc}}^2 + b P_{\text{fc}} + c \quad (16)$$

The cumulative  $\text{H}_2$  consumption error vs. Argonne tests was 1.0%, 1.5%, and 0.7% for Test IDs 61712044, 61712043, and 61712040, respectively.

### E. Battery

The 2017 Toyota Mirai battery is modeled using an equivalent-circuit representation. The terminal voltage  $V_t$  satisfies

$$V_t = V_{\text{oc}} - I_b R_b \quad (17)$$

$V_{\text{oc}}$  is modeled as a function of  $\text{SOC}$  and current. Parameters for  $V_{\text{oc}}$  and  $R_b$  are calibrated from the Toyota Mirai dataset in [29]. The SOC dynamics are:

$$\dot{\text{SOC}} = -\frac{I_b \eta_{\text{bat}}^{\text{sign}(I_b)}}{Q_{\text{bat}}} \quad (18)$$

In this study,  $\eta_{\text{bat}}$  (coulomb efficiency) is set to 0.98, and  $Q_{\text{bat}}$  denotes the battery capacity. Given a battery power request  $P_{\text{bat}}$ , the current is [15]:

$$I_b = \frac{V_{\text{oc}} - \sqrt{V_{\text{oc}}^2 - 4R_b P_{\text{bat}}}}{2R_b} \quad (19)$$

Following our prior procedure in [12], [30], the battery model is driven by logged  $P_{\text{bat}}$  and its state of charge (SOC) was compared with Argonne chassis-dynamometer data [27].

### III. INTEGRATED PLANNER FOR SPEED AND EMS

This section begins with a description of the offline integrated method, which is used to generate the reference speed profile. It then introduces the online integrated framework, designed to handle traffic and varying road surface conditions.

#### A. Offline friction-constrained integrated framework

This subsection presents the integration of speed planning and EMS as a co-optimization and examines the impact of winter road conditions on energy use. For the friction-constrained speed-energy co-optimization (F-COP), a free-driving scenario is considered; realistic cases are addressed later. As shown in the authors' previous work [12], combining speed planning and EMS in an optimal control framework that improves fuel efficiency.  $J(\mathbf{x}, \mathbf{u})$  is the objective function. The control vector  $\mathbf{u} = [j_v, j_{\text{bat}}, j_{\text{fc}}]^T$  includes the jerks of the driving, battery, and fuel cell forces ( $F_v$ ,  $F_{\text{bat}}$ ,  $F_{\text{fc}}$ ). The corresponding powers are  $P_v = F_v v$ ,  $P_{\text{bat}} = F_{\text{bat}} v$ , and  $P_{\text{fc}} = F_{\text{fc}} v$ . According to the FCHEV model, the vehicle state equation,  $\mathbf{x}$ , is given as follows:

$$\frac{d}{dt} \begin{pmatrix} s \\ v \\ m_H \\ \text{SOC} \\ F_v \\ F_{\text{bat}} \\ F_{\text{fc}} \end{pmatrix} = \begin{pmatrix} v \\ \frac{1}{m} (F_v - F_{\text{res}}) \\ a P_{\text{fc}}^2 + b P_{\text{fc}} + c \\ \frac{V_{\text{oc}} - \sqrt{V_{\text{oc}}^2 - 4 R_b P_{\text{bat}}}}{2 R_b Q_{\text{bat}}} \\ m j_v \\ m j_{\text{bat}} \\ m j_{\text{fc}} \end{pmatrix} \quad (20)$$

For offline speed planning, friction brakes are excluded from the dynamics, as the planner does not handle traffic or emergency braking. To incorporate distance-based factors like slope, curvature, and variable speed limits, the state dynamics are expressed in the spatial domain:

$$\frac{dx}{ds} = \frac{dx}{dt} \left( \frac{ds}{dt} \right)^{-1} \quad (21)$$

In the spatial domain, traveled distance ( $s$ ) is the independent variable, time ( $t$ ) replaces  $s$  as the state variable, and can be expressed as:

$$\frac{dt}{ds} = \left( \frac{ds}{dt} \right)^{-1} = \frac{1}{v} \quad (22)$$

The co-optimization aims to minimize total hydrogen use while keeping SOC within limits to prevent unrealistic battery reliance. Final time ( $T$ ) is penalized to discourage slow driving and long trips. The objective function is:

$$J_{\text{co.s}} = \alpha_1 \times H_{2,\text{end}} + \alpha_2 \times \Sigma(\text{SOC} - 0.60)^2 + \alpha_3 T \quad (23)$$

Here,  $\alpha_1$ ,  $\alpha_2$  and  $\alpha_3$  are weight coefficients. Some constraints to mention are:

$$-1 \leq u \leq 1 \quad (24a)$$

$$v_{\min} \leq v \leq v_{\max} \quad (24b)$$

$$\text{SOC}_{\min} \leq \text{SOC} \leq \text{SOC}_{\max} \quad (24c)$$

$$0 \leq F_{\text{fc}} v \leq 114 \text{ kW} \quad (24d)$$

$$-30 \text{ kW} \leq F_{\text{bat}} v \leq +30 \text{ kW} \quad (24e)$$

$$F_v \eta_{\text{pt}}^{-\text{sign}(P_v)} v = F_{\text{fc}} v + F_{\text{bat}} v \quad (24f)$$

Inequality and boundary constraints follow the same logic as in [12]. This subsection focuses on snowy surfaces and road slope.

The offline problem aims to minimize fuel use for a trip between two points in free driving, without considering traffic effects on speed. The distribution of braking force between axles is ignored, assuming regenerative power is unconstrained by it.

1) *Road coefficient effect and winter conditions:* Assuming that the wheels are nonsliding, it is reasonable to assume that When driving on a single-lane road (or when the vehicle is staying in the same lane throughout the trip), the vehicle remains approximately in the middle of its lane. The road is thus defined in terms of curvature of the road center  $\Theta$  calculated from its Cartesian coordinates ( $X$ ,  $Y$ ) as a function of the traveled distance [23]:

$$\Theta(s) = \sqrt{\left( \frac{d^2 X}{ds^2} \right)^2 + \left( \frac{d^2 Y}{ds^2} \right)^2} \quad (25)$$

The tire-force circle is normally used to show the limiting nature of tire-force behavior. An equation for the tire-force circle for a single wheel model can be developed based on the longitudinal and lateral tire forces  $F_x$ ,  $F_y$ , and the normal force of the tire,  $F_z$ :

$$F_x^2 + F_y^2 < (\mu F_z)^2 \quad (26)$$

where  $\mu$  denotes the road adhesion coefficient. Equation (26) can be rewritten based on acceleration. By assuming no or very small side-slipping and an unbanked road, the lateral acceleration can be expressed as:

$$a_y = v^2 \Theta \quad (27)$$

Using longitudinal acceleration,  $a_x$ , from longitudinal dynamics on a flat road results in:

$$a_x^2 + a_y^2 < (\mu g)^2 \quad (28)$$

By considering the effect of road slope as suggested in [31], and a safety factor  $q$  ( $q < 1.0$ ), it can be formulated as:

$$(a_x + g \sin \theta)^2 + a_y^2 < q(\mu g \cos \theta)^2 \quad (29)$$

Equation 29 is used as an inequality constraint for safe driving on sloped roads. For winter conditions, the road adhesion coefficient  $\mu$  is set by surface type: dry asphalt  $\mu \approx 0.7$ –1.0, wet asphalt 0.4–0.6, melting snow 0.25–0.3, ordinary snow 0.2–0.25, fresh snow 0.1–0.2, ice 0.05–0.1 [32], [33]. The value of  $\mu$  can be obtained from V2I, onboard sensors, or weather data [34]. Estimating  $\mu$  is not addressed in this study

#### B. Integrated NMPC

The optimal control problem described earlier provides optimal speed and power allocation for an FCHEV over a given route under slope and winter conditions. However, it does not account for real-world driving, where other vehicles and low computational demand are key factors—a known limitation of

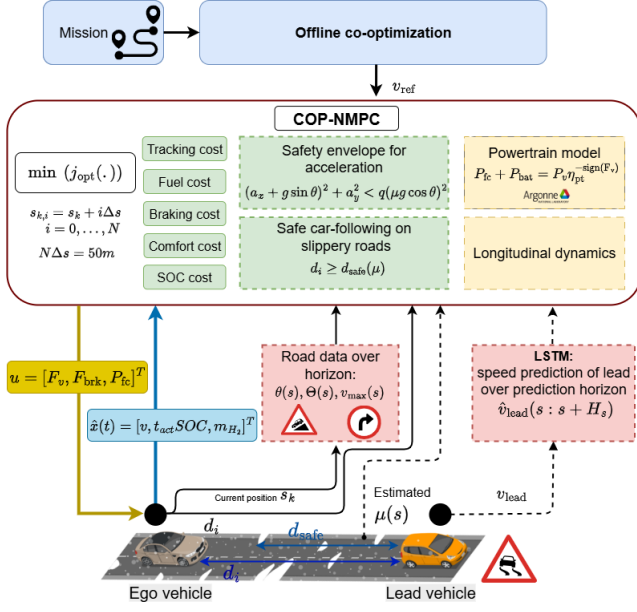


Fig. 2. Structure of the proposed COP-NMPC framework. Parts of the image were created on <https://icograms.com>

integrated speed-EMS optimization [35]. To overcome this, the COP-NMPC framework is introduced, integrating speed planning and EMS through nonlinear model predictive control, as shown in Fig. 2. NMPC manages cost, dynamics, and constraints as general nonlinear functions [36].

A reference speed profile  $v_{ref}$ , obtained from the offline solution, serves as the target for tracking. Vehicle data are assumed available via V2V communication. When no lead vehicle is present, COP-NMPC follows the reference speed; if one is detected, a long short-term memory (LSTM) model predicts its speed over the NMPC horizon. Using this prediction, the ego vehicle maintains a safe distance while optimizing energy use. Slippery winter conditions are also considered for safety. The COP-NMPC, formulated in the spatial domain, jointly optimizes fuel efficiency, comfort, and safety, computing the optimal speed and power split between the battery and fuel cell online.

**1) Lead Vehicle Speed Prediction:** In this study, an LSTM network predicts the lead vehicle's speed, providing input to the constant time headway (CTH) policy that ensures a safe gap between vehicles. The model is trained using the public NGSIM dataset [37]. LSTM, a recurrent neural network (RNN) variant, can selectively retain or discard information and learn complex patterns without the vanishing gradient problem. This enables it to capture sequential dependencies, such as vehicle speed profiles indexed by distance in this work.

The LSTM consists of a forget gate, input gate, output gate, and cell state, as detailed in [38]. In this study, it uses the lead vehicle's speed from the past 50 meters (sampled every 2 meters) to predict the next 50 meters. Given the past  $P$  speed values, the network predicts the next  $H$  as:

$$[v(s_{k+1}), \dots, v(s_{k+H})] = f_{\text{LSTM}}([v(s_{k-P+1}), \dots, v(s_k)]; \zeta) \quad (30)$$

Here,  $f_{\text{LSTM}}(\cdot)$  is the LSTM model with parameters  $\zeta$ , and  $s_k$  denotes the current road position. The network was trained offline using the NGSIM dataset with MATLAB's Deep Learning Toolbox. Standard training was applied without architecture optimization, as LSTM modeling is not the main focus. For background, see [39], [40].

To evaluate performance, 70% of the data was used for training and 30% for validation. The validation RMSE over the 50-meter prediction horizon was 2.589 m/s. As shown in [21], LSTM accuracy decreases with longer prediction windows, and shorter horizons yield better results. In this study, COP-NMPC applies only the first control input at each step, corresponding to a short 2-meter prediction where LSTM error is small. As the controller updates with new data and predictions at every step, only the initial part of the LSTM output affects control. This closed-loop setup limits long-horizon error, keeping the model accurate for its intended role.

**2) Driving safety with friction-adaptive time headway policy:** When the road is clear, the FCHEV follows the reference speed. If a vehicle appears ahead, it maintains a safe following distance (overtaking is not considered). For rural roads with steady traffic, the CTH strategy is sufficient to determine this safe distance [21]:

$$D_{\text{safe}} = th_{\min} \times v + D_0 \quad (31)$$

where  $D_{\text{safe}}$  is the safe following distance,  $D_0 = 2$  m is the constant minimum distance, and  $th_{\min} = 1.5$  s is the minimum time headway. However, the CTH strategy alone is insufficient on slippery roads. To ensure safety on low- $\mu$  surfaces without reducing capacity on dry roads, it is scaled by the inverse of the estimated adhesion coefficient. This adaptive approach is valuable when road adhesion varies along the route.

$$d_{\text{safe}} = th_{\mu} \times v + d_0 \quad (32)$$

The friction-adaptive time headway,  $th_{\mu}$ , is derived from the fact that braking distance under constant friction grows as  $\frac{v^2}{2\mu g}$ . Dividing by  $v$  gives a time margin inversely proportional to  $\mu$ , from which the raw headway time is defined as:

$$th_{\text{raw}} = th_{\min} \times \left( \frac{\mu_{\text{ref}}}{\mu} \right) \quad (33)$$

Here,  $\mu_{\text{ref}}$  is the reference adhesion for dry asphalt, and  $\mu$  is the current value. The inverse relation in  $th_{\text{raw}}$  makes the headway grow as  $\mu$  decreases, providing larger gaps on low-adhesion roads. To avoid extreme gaps, the headway is limited by  $th_{\max}$ , and the final adaptive headway is defined as:

$$th_{\mu} = \begin{cases} th_{\min}, & th_{\text{raw}} \leq th_{\min}, \\ th_{\text{raw}}, & th_{\min} < th_{\text{raw}} < th_{\max}, \\ th_{\max}, & th_{\text{raw}} \geq th_{\max}, \end{cases} \quad (34)$$

After introducing the friction-adaptive time-headway policy, an inequality constraint is considered to limit the gap between the ego and lead vehicle,  $d$ , as:

$$d \geq d_{\text{safe}}(\mu) \quad (35)$$

The initial gap,  $d$ , for NMPC is obtained from the measured bumper-to-bumper distance between the ego and the lead

vehicle, while for the subsequent steps within the NMPC horizon, the predicted lead vehicle speed from the LSTM model,  $v_{\text{lead}}$ , is used to estimate the possible gap between vehicles in the spatial domain:

$$\frac{dd}{ds} = \frac{v_{\text{lead}} - v}{v}. \quad (36)$$

3) *Cost function*: The objective function of the COP-NMPC framework is designed to balance multiple performance criteria: fuel consumption, reference speed tracking, battery SOC regulation, and driving comfort. The cost function can be expressed as:

$$J_{\text{opt}} = \beta_1 J_{\text{tr}} + \beta_2 J_{\text{fuel}} + \beta_3 J_{\text{brk}} + \beta_4 J_{\text{com}} + \beta_5 J_{\text{soc}} \quad (37)$$

Here,  $J_{\text{opt}}$  is the total cost composed of  $J_{\text{tr}}$  (speed tracking),  $J_{\text{fuel}}$  (hydrogen use),  $J_{\text{brk}}$  (friction braking),  $J_{\text{com}}$  (comfort), and  $J_{\text{soc}}$  (SOC deviation).  $\beta_1$ – $\beta_5$  are manually tuned weight coefficients that strongly influence results. A detailed sensitivity analysis of these and other parameters is left for future work.

The reference speed,  $v_{\text{ref}}$ , is provided by the offline co-optimization framework present in the previous section and is formulated as:

$$J_{\text{tr}} = \sum_{k=0}^{N_{\text{mpc}}} (v_k - v_{\text{ref}})^2 \quad (38)$$

$J_{\text{fuel}}$  represent the accumulated hydrogen consumption:

$$J_{\text{fuel}} = H_2(N_{\text{mpc}} + 1) \quad (39)$$

It is assumed that the friction brake only applies after saturation of the regenerative brake. The friction brake force,  $F_{\text{brk}}$ , is penalized to minimize its use and ensure that the deceleration force remains within the regenerative region of the electric motor:

$$J_{\text{brk}} = \sum_{k=0}^{N_{\text{mpc}}} (F_{\text{brk}})^2 \quad (40)$$

To ensure smooth driving and ride comfort, a cost related to rapid fluctuations in the longitudinal force is introduced as:

$$J_{\text{com}} = \sum_{k=0}^{N_{\text{mpc}}-1} (F_{v,k+1} - F_{v,k})^2 \quad (41)$$

An SOC-related cost is defined to keep the SOC within a reasonable range and to prevent excessive dependence on the battery:

$$J_{\text{soc}} = \sum_{k=0}^{N_{\text{mpc}}} (\text{SOC}_k - 0.60)^2 \quad (42)$$

4) *COP-NMPC optimization and horizon*: This subsection formulates the COP-NMPC in the spatial domain, defining the vehicle states, decision variables, and constraints for speed–energy co-optimization. The formulation captures both vehicle dynamics and powertrain behavior. The state equations include four states:  $v$ ,  $\text{SOC}$ ,  $t$ , and  $m_{H_2}$ , which directly

govern motion, power split, and energy flow between the fuel cell and battery, expressed as:

$$\frac{d}{ds} \begin{pmatrix} v \\ t \\ m_{H_2} \\ \text{SOC} \end{pmatrix} = \begin{pmatrix} \frac{1}{mv} (F_v - F_{\text{brk}} - F_{\text{res}}) \\ \frac{1}{v} \\ \frac{1}{v} (a(P_{\text{fc}})^2 + bP_{\text{fc}} + c) \\ \frac{V_{\text{oc}} - \sqrt{V_{\text{oc}}^2 - 4R_b P_{\text{bat}}}}{2R_b Q_{\text{bat}} v} \end{pmatrix} \quad (43)$$

The decision vector includes the longitudinal force, friction brake force, and fuel cell force,  $u_{\text{mpc}} = [F_v, F_{\text{brk}}, F_{\text{fc}}]^T$ . As noted earlier,  $F_{\text{fc}}$  converts to fuel cell power via  $P_{\text{fc}} = F_{\text{fc}}v$ . Unlike the offline method, battery power is not directly controlled but passively handled through an equality constraint from Equation 24f. To avoid rapid fluctuations in fuel cell power, a constraint is imposed on how much the fuel cell power can change between consecutive spatial nodes. This step-to-step variation is bounded as:

$$|\Delta F_{\text{fc},k}| \leq \Delta F_{\text{fc},\text{max}} \quad (44)$$

The electric motor torque is subject to the following constraints, as expressed in Equation 10:

$$\tau_{\text{min}} \leq \tau \leq \tau_{\text{max}} \quad (45)$$

The friction brake force is constrained:

$$0 \leq F_{\text{brk}} \leq F_{\text{brk},\text{max}} \quad (46)$$

The objective function, as defined in Equation 37, balances tracking performance, hydrogen consumption, braking penalties, and comfort, as previously described. Taking into account the constraints, system dynamics, and objective function, the COP-NMPC problem can be formulated as:

$$\begin{aligned} & \min_{F_v, F_{\text{fc}}, F_{\text{brk}}} \quad (37) \\ & \text{s.t. :} \\ & (24b), (24c), (24d), (24e), (24f) \\ & (29), (35), (36), (43), (44), (45), (46) \end{aligned} \quad (47)$$

At each time interval, the vehicle's current distance is passed to the COP-NMPC. The distance-related parameters for the horizon length are then extracted and fed into the COP-NMPC. Next, the optimal control commands for a 50-meter horizon are computed, and the first elements of the control variables are applied to the vehicle. The 50-meter horizon length is chosen as a trade-off between computational efficiency and sufficient foresight for safe, energy-efficient maneuvers. At each iteration, the latest measured state values and the previously generated control inputs are used as a warm start for the optimization, as initializing from the previous solution significantly reduces the number of required solver iterations. Warm-starting is particularly important in NMPC because it accelerates solver convergence, making the optimization process more suitable for real-time applications. This process repeats until the final destination is reached.

Emergency braking dynamics have been addressed in other studies [32], [33] and are not included in the present work.

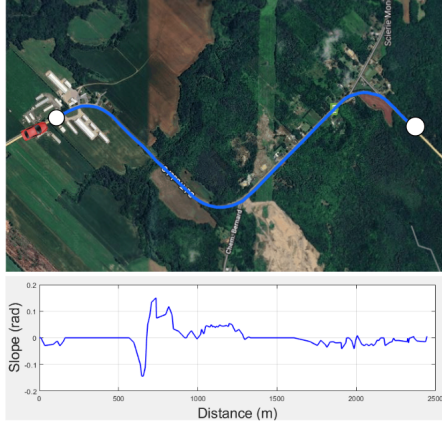


Fig. 3. The road section used in this study with the corresponding road slope.

#### IV. RESULTS AND DISCUSSION

To underline the effectiveness of the proposed friction-aware COP and COP-NMPC, the results are presented in two steps. First, the co-optimization of speed and energy under friction limits, considering different road adhesion coefficients, is evaluated through simulation and compared with a benchmark curvature-based speed planning method that uses a fixed lateral acceleration to determine the maximum speed. In the next step, a hardware-in-the-loop (HIL) setup is employed to demonstrate the online performance of the COP-NMPC. The results from the online method are then compared with the offline full-preview optimal control, which serves as the benchmark.

To ensure flexibility in development and simplify implementation, the OCP is formulated within the CasADi framework [41] and solved using IPOPT interior-point solver [42]. Non-smooth functions, such as the sign function, were replaced with smooth approximations, resulting in a trade-off between smoothness and the accuracy of the representation.

##### A. The effect of road adhesion coefficient

A 2.4 km section of a rural road in Quebec is used for this study (Fig. 3). The road has low traffic and long winter coverage of ice and snow, matching the conditions targeted in this work. Geometry data from Google Maps are converted into a curvature model, and slope is extracted separately. The trip starts and ends from rest.

To assess the effect of road adhesion on F-COP speed profiles, simulations are performed for  $\mu$  values from 0.1 to 1.0, spanning icy to dry conditions. The resulting speed profiles appear in Fig. 4, while Fig. 5 shows the corresponding changes in trip time and hydrogen use. As  $\mu$  increases, the feasible speed envelope expands. For  $\mu \leq 0.3$ , the friction constraint dominates, yielding low, wavy profiles with sharp drops at curvature hot spots. Around  $\mu \approx 0.4$ , speeds on straights reach the 80 km/h limit, while dips persist in curves. For  $\mu \geq 0.5$ , the profiles converge, limited mainly by other constraints. The remaining dips occur at tight curves where lateral acceleration governs the friction circle.

Trip time drops quickly as  $\mu$  rises from 0.1 to 0.3, then levels off beyond  $\mu \approx 0.4$ . Hydrogen use shows the reverse

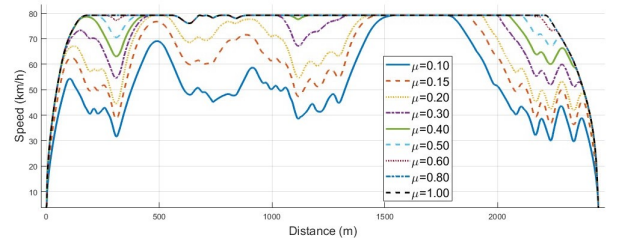


Fig. 4. Effect of Road Adhesion Coefficient on Speed Profile.

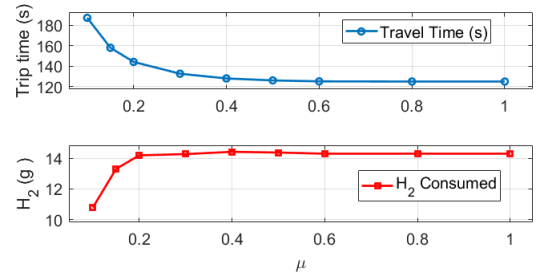


Fig. 5. Effect of Road Adhesion Coefficient on Trip Time (top), and Hydrogen Consumption (bottom).

trend, increasing steeply up to 0.3 and then stabilizing with a slight dip at higher  $\mu$ . At high  $\mu$ , greater grip enables faster cornering and stronger acceleration, cutting trip time but raising energy use. Around  $\mu \approx 0.4$ – $0.5$ , the limits shift to  $v_{\max}$ ,  $a_{\max}$ , and motor torque rather than tire grip, so extra adhesion yields minimal time gains and negligible fuel increase.

##### B. Real-time and hardware in the loop application

In a real-world scenario, it is crucial to account for other vehicles on the road. Here, COP-NMPC optimizes speed and energy management on the same route as before, with a lead vehicle introduced to challenge the ego FCHEV to maintain safe spacing rather than follow the reference speed. Real-time performance is verified through a HIL test using the OPAL-RT OP5707XP simulator, where the controller runs on the host PC and the plant model on the real-time simulator. The host PC is x86-based with an Intel Core i7-10700 CPU and 32 GB RAM. Road geometry and vehicle states (position, velocity, SOC, and hydrogen consumption) are received from OPAL-RT at 10 Hz. Each solve starts from the previous optimal solution when available; otherwise, a zero-order hold with constant initial states is used. To limit computation, the solver allows up to 50 iterations before moving to the next optimization. The resulting solution is then sent to the OPAL-RT system. For comparison, the COP-NMPC results are evaluated against an offline full-preview optimal control benchmark that was solved once over the entire route with perfect knowledge of road/traffic and constraints. It yields the global minimum cost.

1) *Results and Analysis of speed profile and car following:* Fig. 7 shows the COP-NMPC speed profile (solid red), the reference from the previous section (dashed black), and the lead vehicle speed for the HIL test (dotted blue). At the start, the lead moves slower than the reference, so the NMPC

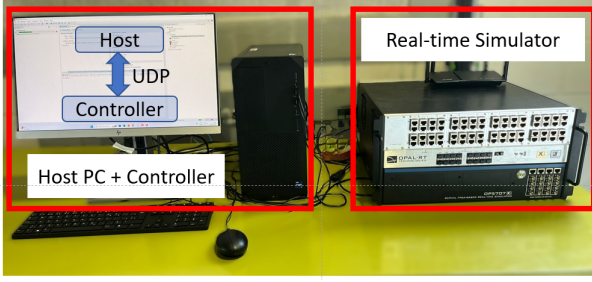


Fig. 6. HIL test setup.

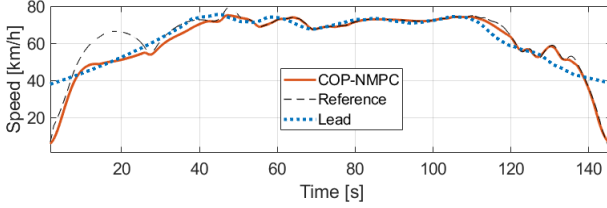


Fig. 7. Comparison of COP-NMPC speed profile, reference profile, and lead vehicle speed.

prioritizes car-following, accelerating only enough to establish a safe gap while staying below the reference speed. When the lead vehicle accelerates, the FCHEV follows, showing that the safety constraint, not the reference speed, governs control in this phase. After 45 seconds, the lead vehicle decelerates slightly, and the NMPC promptly lowers the FCHEV's speed to maintain headway while using any slack to stay near the reference speed.

Near the end of the route, both the lead and reference vehicles decelerate. The lead vehicle slows to around 40 km/h and maintains that speed, while the FCHEV continues to decelerate to a full stop, as required by the trip scenario. Figure 8 shows that the trajectories of the ego and lead vehicles remain closely aligned for most of the route, indicating that the NMPC effectively maintains safety and mission progress.

Fig. 9 compares the ego vehicle speed from the COP-NMPC with that from the offline full-preview benchmark along the route. The two profiles match closely over most distances. This indicates that the online controller has the same behavior as the benchmark behavior. On straight sections, both profiles maintain the same cruise speed, and the terminal deceleration aligns. In short, the benchmark forms a slightly more aggressive profile in segments where extended preview is more beneficial.

## 2) Results and Analysis of EMS and fuel consumption:

Fig. 10 shows the electric power balance and SOC during the HIL run. The top plot presents total, fuel-cell, and battery power; the bottom shows SOC. At launch, demand rises rapidly, with the battery supplying transients and the fuel cell staying low. As SOC drops from 0.60, the fuel cell supplies the main load while the battery manages peaks and regeneration. Between 40 s and 80 s, braking causes small SOC rises. After 80 s, the fuel cell powers the system and recharges the battery, steadily increasing SOC. In the final section, short acceleration-braking events make the battery the main source

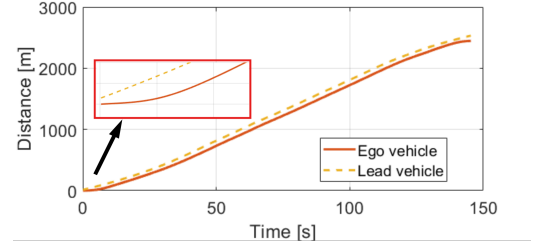


Fig. 8. Comparison between CTH strategy and proposed method (top), and ego and lead location along the path (bottom)

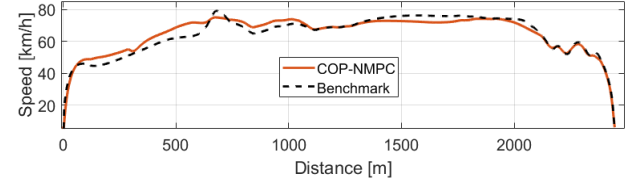


Fig. 9. Comparison between COP-NMPC and the offline full-preview optimal control benchmark.

and further recharge it. Overall, the fuel cell handles steady demand, the battery handles transients, and SOC is restored to target.

Fig. 11 compares COP-NMPC with the offline benchmark in terms of SOC (top) and cumulative (bottom) along the route. COP-NMPC draws the battery down early, and SOC falls from 0.60 to about 0.54 within the first kilometer. The benchmark keeps SOC higher for longer, then lets it decline later and restores it only in the last 500 m. The cumulative  $H_2$  curves show these operating patterns. COP-NMPC uses little  $H_2$  early as the battery handles transients, then increases fuel-cell power mid-route to propel the vehicle and restore SOC, causing a steep rise. The benchmark spreads fuel-cell use more evenly, giving a gentler slope. Total  $H_2$  use is 13.285 g for COP-NMPC and 11.841 g for the benchmark, a 12.2% increase consistent with the benchmark's full preview and COP-NMPC's finite-horizon control.

3) *Computation time:* To assess real-time feasibility, the distribution of solver wall times per MPC iteration was analyzed. The results showed that, with a computation budget of 100 ms ( $dt = 0.1$  s), 99.86% of the iterations were completed within the allowed time, and the median computation time was 26.2 ms, confirming that the solver performance meets real-time requirements.

4) *COP-NMPC with varying road friction:* In the presented results,  $\mu$  is assumed constant for simplicity. However, the proposed method can handle variations of  $\mu$  at each 2 m interval, adjusting speed for safe and energy-efficient driving based on the local coefficient. Fig. 12 shows the speed profile for a road with varying  $\mu$ .

5) *Initial SOC variation:* Results were obtained for missions with different initial SOC. When starting below the reference, the EMS raises the fuel-cell output and limits battery discharge so SOC recovers, using the battery mainly for transients and the fuel cell for steady load and charging. When starting above the reference, the EMS lets the battery supply traction longer, allowing SOC to drop toward 0.60

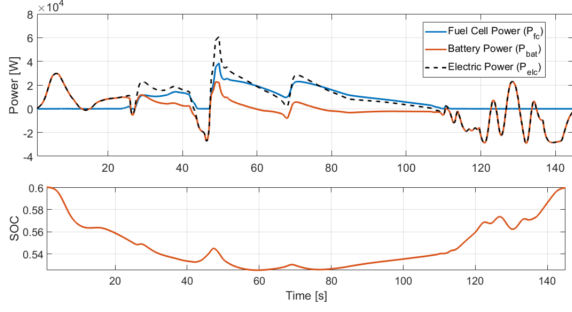


Fig. 10. EMS power split and SOC trajectory.

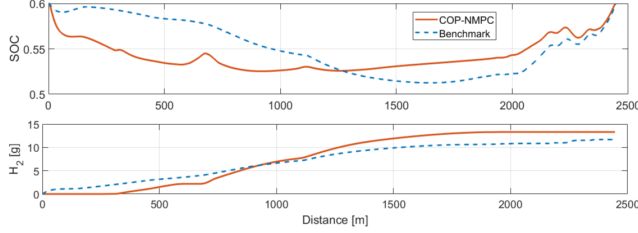


Fig. 11. EMS power split and SOC trajectory.

TABLE III  
COMPARISON OF  $H_2$  CONSUMPTION BETWEEN COP-NMPC AND BENCHMARK.

| Case | COP-NMPC<br>(g) | Benchmark<br>(g) | Excess<br>(%) |
|------|-----------------|------------------|---------------|
| 1    | 13.28           | 11.84            | 12.2          |
| 2    | 37.80           | 33.89            | 11.5          |

before returning to nominal. This saves early hydrogen at the cost of higher battery use. In all cases, final SOC values match the reference, keeping hydrogen-use comparisons fair. The strategy thus adapts sensibly to initial SOC while meeting safety and drivability limits. Fig. 13 shows SOC evolution for different initial values and the corresponding power split.

6) *Additional case study:* A second 4920-meter route with steeper uphill and downhill sections was used for comparison. Table III compares COP-NMPC and the benchmark on both routes under identical constraints. In each case, COP-NMPC achieves the same end-SOC as the benchmark. The use of two contrasting routes confirms that performance is not route-dependent, as the controller consistently balances fuel-cell and battery work while planning safe, energy-efficient speeds.

## V. CONCLUSIONS

This study proposes an online integrated optimization of speed planning and EMS for an FCHEV, capable of addressing the challenges of driving on hilly roads in winter conditions. The proposed method (COP-NMPC) aims to reduce fuel consumption, ensure safe maneuvers on slopes under slippery conditions, and enable secure car-following in winter by jointly planning efficient speed profiles and power allocation between the battery and fuel cell.

First, the effect of including slippery roads in the integrated optimization of speed and EMS was highlighted. It was shown that in the critical zone, where the road adhesion coefficient

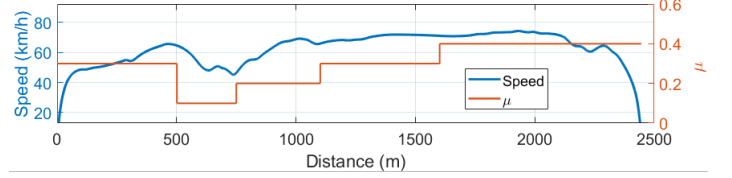


Fig. 12. Speed profile on a road with varying  $\mu$  values.

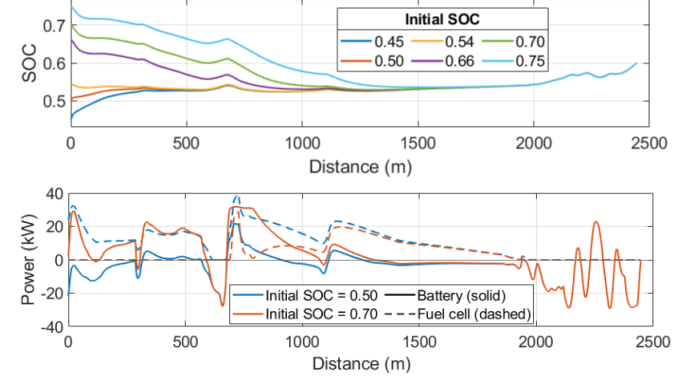


Fig. 13. SOC profiles for different initial SOC values (up) and power plots of battery and fuel cell for high and low initial SOC (bottom).

is between 0.1 and 0.4, hydrogen consumption can vary by about 33% and travel time by 31%.

The COP-NMPC can adapt to changing road adhesion coefficient values in real-world scenarios and provide a secure speed profile by incorporating road surface condition, road slope, road curvature, and the headway distance to the lead vehicle. This enables the planning of safe profiles in winter conditions, which have been largely overlooked in the literature. While COP-NMPC consumed about 12.2% and 11.5% more fuel on two separate road sections compared to an offline benchmark, it demonstrated good suitability for online application as a planning layer. With the planner's time budget strictly set to 100s, the MPC median solving time was around 26ms. The robustness and reliability of the strategy to changes in initial SOC, road adhesion coefficient, and different routes were demonstrated through multiple tests.

Future work could explore the application of the proposed strategy to multi-vehicle car-following and platooning. In addition, the study could be extended to examine the impact of the proposed strategy on fuel cell health and degradation under winter conditions.

## VI. ACKNOWLEDGMENT

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### 4.3 Concluding Remarks

This chapter extended the integrated speed planning and energy management framework from an offline, free-driving formulation to a real-time, traffic-aware approach. The proposed NMPC formulation was shown to effectively handle varying road slope, curvature, and adhesion coefficients, enabling the vehicle to generate safe and energy-efficient trajectories on slippery winter roads. Furthermore, by incorporating lead-vehicle prediction through an LSTM-based model and introducing a friction-adaptive car-following strategy, the framework ensured safety under realistic traffic scenarios where braking distances are strongly affected by road conditions.

Based on the hardware-in-the-loop experiments conducted in this study, the proposed COP-NMPC framework can be executed in real time on a standard automotive-grade computing platform. The controller was tested on an x86-based processor comparable to mid-range onboard CPUs commonly used in autonomous vehicles, without relying on dedicated GPUs or specialized accelerators. With a control update period of 100 ms, the optimization consistently converged within the available time budget, with a median computation time of approximately 26 ms. These results indicate that the proposed approach can be deployed on conventional embedded processors used for vehicle planning and control, provided that solver warm-starting and moderate optimization horizons are employed.

Compared to the full-preview offline benchmark, the online method required slightly higher energy consumption but maintained real-time feasibility while ensuring safety and drivability. These results confirm that the integrated NMPC framework is a practical and robust solution for autonomous fuel cell hybrid electric vehicles in challenging winter environments.



## **Chapter 5 - Conclusion**

This thesis explored the development and refinement of energy-efficient driving strategies for FCEVs, with a focus on optimizing both vehicle speed profiles and power distribution. Conventional approaches to energy management typically rely on simplified vehicle models and treat speed planning and EMS separately, which leads to sub-optimal solutions. In addition, the influence of real-world factors such as road slope, limited traction on slippery winter roads, and the need for real-time implementation has often been overlooked. To address these gaps, the thesis proposed a set of methods that balance efficiency, realism, and practical applicability. The contributions of the individual articles can be summarized as follows:

The first article established a foundation by reviewing the current state of energy recovery and energy harvesting technologies in electric and fuel cell vehicles. It highlighted key methods such as regenerative braking, suspension-based harvesting, and thermal energy recovery. This review not only provided a technical background but also identified critical gaps in system integration and control, setting the direction for the original research in the following chapters.

The second article proposed an improvement to the conventional sequential optimization approach by introducing a dynamic deceleration constraint during speed planning. This constraint adapts to the vehicle's regenerative power limits and helps avoid braking scenarios that exceed energy absorption capacity. The study demonstrated that even in a sequential framework, incorporating powertrain-aware constraints during motion planning can yield measurable improvements in energy recovery and fuel economy.

The third article presented a unified co-optimization framework that simultaneously solves for the optimal speed trajectory and power allocation between the fuel cell and

battery. This integrated approach outperformed the sequential method across various driving scenarios. It achieved better fuel efficiency and smoother energy management, confirming the benefits of addressing vehicle motion and energy flow in a single, cohesive optimization problem. This article represents the core technical contribution of the thesis and forms the basis for future control-oriented implementations.

The fourth article (in preparation) extends the co-optimization approach to a real-time MPC framework capable of adaptive behavior in dynamic traffic. By incorporating car-following constraints and road-tire friction limitations, this work aims to make the strategy suitable for real-world deployment. The MPC controller adjusts its decisions based on traffic flow and road conditions, ensuring both energy efficiency and safety.

The approaches introduced in this study can be scaled for application to heavy-duty fuel cell vehicles or for training AI models designed to control vehicle motion and EMS simultaneously.

In summary, the thesis delivers a complete trajectory from theoretical review to practical, real-time applications of energy-efficient driving strategies in FCEVs. It demonstrates how careful integration of physical constraints, predictive modeling, and control theory can significantly improve fuel economy without compromising drivability. The progression from offline optimization to real-time control also reflects a growing need for adaptive and intelligent systems in the next generation of electrified vehicles.

## **5.1 Recommendations for Future Directions**

While this thesis has presented a structured path from theoretical review to integrated and real-time optimization strategies for FCEVs, it also opens the door to several new possibilities. Moreover, as vehicle electrification advances and intelligent systems become

more common, the opportunity to build on this work and extend it to broader applications is both relevant and timely.

To continue the progress made in this research, several promising directions are proposed:

*5.1.1 Recommendation 1: Incorporate Long-Term Forecasting and Eco-Routing into the Optimization Framework*

As it is shown in Table 5-1, optimizing a transport system consists of different levels. While the current thesis focuses primarily on local or short-horizon optimization, another promising direction is the integration of long-term forecasting into the co-optimization framework. Most vehicles are equipped with GPS, navigation systems, and access to cloud-based traffic data. Leveraging this information can allow the control system to make decisions that minimize energy consumption over an entire trip rather than only responding to immediate conditions.

Table 5-1 Separation of Traffic Flow Dynamics from Vehicular Dynamics and Transportation Planning [1].

| <b>Time Scale</b> | <b>Field</b>          | <b>Models</b>        | <b>Aspect of Traffic (examples)</b> |
|-------------------|-----------------------|----------------------|-------------------------------------|
| < 0.1 s           | vehicle dynamics      | sub-microscopic      | control of engine and brakes        |
| 1 s               |                       |                      | reaction time, time gap             |
| 10 s              |                       |                      | acceleration and deceleration       |
| 1 min             | traffic flow dynamics | car-following models | acceleration and deceleration       |
| 10 min            |                       | macroscopic models   | cycle period of traffic lights      |
|                   |                       |                      | stop-and-go waves                   |
| 1 h               | transportation        | route assignment     | peak hour                           |
| 1 day             |                       | traffic demand       | daily demand pattern                |
| 1 year            |                       |                      | building/changing infrastructure    |
| 5 years           | planning              | statistics           | socioeconomic structure             |
| 50 years          |                       | age pyramid          | demographic change                  |

The integration of eco-routing is a key component of this idea. Instead of simply optimizing the vehicle's behavior along a predefined path, the vehicle can optimize its path and behavior together, selecting roads that offer smoother traffic flow, fewer stops, or less elevation gain to reduce energy consumption.

To move toward this recommendation, the following research components are suggested:

- Couple the offline method with a trip-level optimization layer that selects the most energy-efficient route based on traffic forecasts, road topology, and driving style constraints.
- Use machine learning techniques to forecast traffic density and road conditions several kilometers ahead, feeding this into the lower-level MPC for real-time planning.
- Evaluate trade-offs between fuel efficiency, trip time, and driver preferences, allowing dynamic adjustment of optimization priorities (e.g., prioritizing range in low battery scenarios or speed under time pressure).

This two-layered structure, combining long-horizon eco-routing and short-horizon MPC, aligns well with intelligent mobility systems and can significantly reduce total fuel or hydrogen consumption in connected environments.

#### *5.1.2 Recommendation 2: Expand the Car-Following Model to Handle Dense Traffic and Complex Multi-Agent Scenarios*

The current implementation includes a basic car-following mode triggered by proximity to a lead vehicle. However, real-world driving involves much more complex traffic patterns,

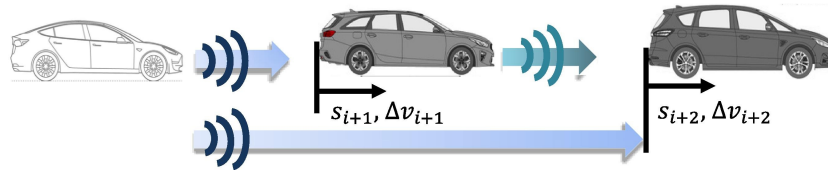


Figure 5.1 Car-following with multiple lead vehicles [2].

including interactions with multiple surrounding vehicles, lane changes, and external control signals like traffic lights. Expanding the car-following model to better represent dense urban traffic or highway platooning would significantly increase the realism and robustness of the system.

The following research extensions are recommended:

- Model the ego vehicle's interaction with more than one lead vehicle using multi-agent prediction frameworks, considering worst-case behaviors and stochastic motion patterns.
- Incorporate traffic signal timing and stop signs into the prediction horizon, integrating this data from infrastructure communication or vehicle-to-everything (V2X) networks.
- Add constraints or penalties to enforce safety distances and smooth speed adjustments in response to highly dynamic traffic flow, simulating congestion or intersection behaviors.

This direction brings the proposed framework closer to deployment in real-world autonomous or semi-autonomous driving scenarios.

### *5.1.3 Recommendation 3: Integrate Powertrain Aging Models into the Co-Optimization Framework*

The current co-optimization framework prioritizes fuel economy and system efficiency without explicitly considering long-term degradation effects on key components such as the fuel cell and battery. In real-world scenarios, aging impacts both performance and reliability, especially in vehicles subject to repeated charge–discharge cycles or high-power transients. Incorporating component aging models into the optimization process would yield control strategies that are not only energy-efficient but also health-aware and durability-oriented.

This approach ensures that the vehicle’s control system accounts for degradation and aging, thereby balancing short-term performance with long-term operational cost and reliability.

To move toward this recommendation, the following steps are suggested:

- Develop degradation models for the battery and fuel cell subsystems, including cycle aging, temperature effects, and voltage drift, based on empirical or semi-empirical models.
- Introduce these aging metrics into the cost function or as constraints, such as penalizing excessive current draw or state-of-charge swings that accelerate degradation.
- Perform a comparative analysis between fuel-optimal and health-optimal strategies under identical driving conditions to quantify the trade-off between efficiency and longevity.

- Investigate the impact of predictive aging-aware strategies in online MPC setups, particularly during aggressive driving scenarios or under thermal stress.

This research direction could enhance the long-term viability of hydrogen-powered electric vehicles and align the energy management system with reliability and maintenance objectives.

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## Appendix A - Rationale for Direct Optimal Control

Direct methods replace the original continuous-time optimal control problem (OCP) with a finite-dimensional nonlinear program (NLP) that can be solved using mature optimization methods. These methods are especially effective when:

- the system dynamics are highly nonlinear or hybrid in nature,
- constraints apply simultaneously to states and controls,
- high-accuracy derivatives are available.

By discretising first and optimising second, we gain access to large-scale sparse NLP solvers. The trade-off is that the infinite-dimensional control problem is reduced to a mesh-dependent finite problem. When the mesh is refined adaptively, convergence to the continuous-time solution is guaranteed under relatively mild regularity conditions.

## From Differential Equations to NLPs

A generic OCP is defined as:

$$\begin{aligned} \min_{u(\cdot)} J &= \Phi(x(t_f)) + \int_{t_0}^{t_f} L(x(t), u(t)) dt \\ \text{s.t. } \dot{x} &= f(x, u), \quad x(t_0) = x_0, \quad g(x(t), u(t)) \leq 0, \quad h(x(t), u(t)) = 0 \end{aligned}$$

The transcription process involves the following steps:

1. **Mesh generation:** divide the time horizon  $[t_0, t_f]$  into  $N$  intervals. The spacing may be uniform or adapted.

2. **State and control parameterisation:** represent trajectories using piecewise-constant, linear, or higher-order polynomials.
3. **Dynamics enforcement:** impose defect constraints to enforce the dynamics (see Section 3).
4. **Cost approximation:** replace the integral with a quadrature rule appropriate to the mesh.
5. **Constraint assembly:** stack all constraints — including dynamics, path limits, and boundaries — into a single algebraic vector  $F(z)$ .
6. **Optimization:** minimize  $J(z)$  subject to  $F(z) = 0$  and bounds  $C \leq z \leq D$ .

Here,  $z$  collects all decision variables: nodal states, controls, and possibly additional static parameters. The result is a sparse NLP whose structure reflects the local coupling of the discretisation; CasADi automatically exploits this sparsity.

## Discretisation Schemes in Direct Methods

Several schemes are used to transcribe continuous-time dynamics into algebraic constraints for numerical optimisation. The most common ones include [60]:

**Euler and Trapezoidal Methods:** These are low-order, time-marching methods. Forward or backward Euler is first-order, while the trapezoidal rule offers second-order accuracy.

$$x_{k+1} - x_k - \frac{\Delta t}{2}(f_k + f_{k+1}) = 0$$

**Hermite–Simpson and Radau Collocation:** These higher-order collocation schemes achieve better accuracy per mesh point. Hermite–Simpson enforces dynamics at both midpoints and endpoints, while Radau and Gauss–Legendre schemes achieve spectral accuracy. These methods directly impose defect constraints and assemble a system of equations that approximate the ODE.

## Multiple Shooting

In contrast to collocation, multiple shooting divides the horizon into segments and integrates the dynamics over each using a numerical ODE solver. The decision variables are the initial conditions for each interval, and continuity is enforced by matching end states across intervals. This approach introduces fewer defect constraints but enlarges the decision vector. It also handles hybrid dynamics, algebraic constraints, or discontinuities more naturally. Multiple shooting is especially beneficial for systems with abrupt changes.

## Constructing Sparse NLPs with CasADi

CasADi is a symbolic framework for numerical optimisation that builds computational graphs for user-defined functions and provides exact derivatives using algorithmic differentiation (AD) [61]. It plays a central role in the transcription and solution of the optimal control problems addressed in this thesis.

### Symbolic Variable Declaration

Decision variables could be declared through the `Opti` stack. For instance, a set of  $N + 1$  state vectors and  $N$  control inputs can be defined as follows:

```

opti = casadi.Opti()
X = opti.variable(nx, N+1)    # states
U = opti.variable(nu, N)      # controls

```

## Dynamics Defects

In the multiple shooting approach, system dynamics are integrated explicitly over each interval using a numerical integrator (e.g., Runge–Kutta or Euler). Instead of directly enforcing a discretised differential equation, the predicted state at the end of each interval is computed via integration and matched to the next decision variable. The resulting matching condition ensures trajectory continuity:

```

for k in range(N):
    x_k      = X[:, k]
    u_k      = U[:, k]
    x_next   = X[:, k+1]
    x_pred   = F(x_k, u_k) ['xf']          # forward integrate once
    opti.subject_to( x_next - x_pred == 0 )

```

Here,  $F$  is a CasADi integrator function representing the continuous dynamics over one time step. This approach separates the integration from the optimisation variables and introduces fewer dynamic constraints, which can be advantageous for stiff systems or those with discontinuities.

## Objective Function

A typical stage cost might penalise control effort and include a terminal cost on the final state:

```
J = casadi.sumsqr(U) * dt + terminal_cost(X[:, -1])
opti.minimize(J)
```

## Sparsity Exploitation

CasADi automatically propagates the sparsity structure of the problem. Each defect constraint depends only on  $x_k$ ,  $x_{k+1}$ , and  $u_k$ , resulting in a Jacobian with a block-banded pattern. This structure is communicated to the solver (e.g., IPOPT) using compressed row storage (CRS), enabling efficient linear algebra operations without requiring manual specification by the user.

## A.1 Interior-Point Optimizer (IPOPT): Core Algorithm

IPOPT (Interior Point OPTimizer) is an open-source solver for large-scale NLP, based on a primal-dual interior-point method. It solves constrained problems using a logarithmic-barrier approach with filter-based globalization.

### Barrier Problem

Inequality constraints  $g(z) \leq 0$  are incorporated into the objective by adding a barrier term to the Lagrangian:

$$\mathcal{L}_\mu(z) = \mathcal{L}(z) - \mu \sum_i \log(-g_i(z)),$$

where  $\mu > 0$  is the barrier parameter. As  $\mu \rightarrow 0$ , the solution of the barrier problem converges to the solution of the original constrained problem.

## KKT System

At each iteration, IPOPT solves the Karush–Kuhn–Tucker (KKT) system:

$$\begin{bmatrix} \nabla_{zz}^2 \mathcal{L} & \nabla g^T \\ \nabla g & 0 \end{bmatrix} \begin{bmatrix} \Delta z \\ \Delta \lambda \end{bmatrix} = \begin{bmatrix} -\nabla_z \mathcal{L} \\ -g(z) \end{bmatrix}.$$

Here,  $\nabla_{zz}^2 \mathcal{L}$  is the Hessian of the Lagrangian. IPOPT uses an exact Hessian by default.

## Linear Solver

The linear KKT system is factorised using external sparse solvers such as MUMPS, MA57, PARDISO, or HSL. The choice of solver affects both performance and numerical robustness. CasADi passes the selected backend using the option:

```
ipopt.linear_solver = "mumps"
```

## Filter Line Search

IPOPT employs a filter method to globalise the search: trial steps are accepted if they either reduce constraint violation or decrease the objective function. This approach avoids poor scaling and ill-conditioning as the barrier parameter  $\mu$  becomes small.

## Adaptive Barrier Update

The barrier parameter  $\mu$  is reduced whenever the current iterate is sufficiently central and feasible. A typical update rule is:

$$\mu_k = \alpha \mu_{k-1}, \quad \alpha \approx 0.2.$$

The update strategy is configured by the `mu_strategy` option and can be set to either `monotone` or `adaptive`.

## Convergence Criteria

The algorithm terminates when the following conditions fall below user-defined tolerances:

- Primal feasibility,
- Dual feasibility,
- Complementary slackness.

## A.2 IPOPT in CasADi: Interface and Key Options

IPOPT is seamlessly integrated into the CasADi `Opti` stack and is configured using solver options at the time of declaration.

### 6.1 Basic Invocation

The solver is instantiated with a dictionary of options, passed to `opti.solver`:

```
opti.solver('ipopt', {
    'ipopt.tol':          1e-6,
    'ipopt.max_iter':     3000,
    'ipopt.linear_solver': 'ma57', # or 'mumps'
    'ipopt.mu_strategy':  'adaptive',
    'ipopt.mu_init':      0.1,
```

```

        'ipopt.hessian_approximation': 'exact'
    })

sol = opti.solve()

```

The tolerances and strategies should be selected based on problem scale, stiffness, and convergence sensitivity. A maximum iteration count of 3000 is typically generous enough for convergence while remaining computationally feasible.

## Warm Starts

In model predictive control (MPC) and online optimization loops, warm-starting from the previous solution significantly reduces the iteration count.

- **Primal variables:**

```

opti.set_initial(X, x0_prev)
opti.set_initial(U, u0_prev)

```

- **Dual variables and multipliers:**

```

opti.set_initial(opti.lam_g, lam_g_prev)    # constraints
opti.set_initial(opti.lam_p, lam_p_prev)    # parameters

```

- **Option enabling warm start:**

```

'opti.warm_start_init_point': 'yes'

```

This option enables IPOPT to use the provided initial points not only as a guess for primal variables, but also for the slack and dual variables.