Green Driving Innovative Methods to Minimize Energy Consumption in Hybrid Electric Vehicles

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ABSTRACT

This paper presents the modelling and control of a hybrid electric vehicle powertrain. The powertrain, which has a series-parallel hybrid topology, was used as a case study. Mathematical models were developed for the internal combustion engine, electric motors, batteries and vehicle dynamics. A computational model was implemented in Matlab/Simulink and validated against experimental data, showing good agreement for fuel consumption. A rules-based control strategy was developed to approximate the logic used in the real vehicle. Global powertrain optimisation was then conducted using dynamic programming to minimise fuel consumption. Two cases were analysed, one optimising only the torque distribution and another also optimising the operating points of the internal combustion engine. The optimal control resulted in 9.5% and 10% lower fuel consumption than the non-optimal strategy, demonstrating the potential for consumption reduction. The results illustrate the importance of optimising multiple degrees of freedom in the powertrain and not only confining the

engine to its optimal operating line. This study provides a methodology for developing optimal control strategies for hybrid vehicles using easily implementable tools. The findings highlight the importance of synergizing technology with informed driving habits to support global sustainability goals.

Keywords: Hybrid electric vehicles, Powertrain modeling, Dynamic programming, Optimal control, Fuel consumption

1. Introduction

Hybrid electric vehicles (HEVs) have gained popularity in recent years due to their potential for reducing fuel consumption and emissions compared to conventional vehicles. HEVs combine an internal combustion engine and electric motor(s), allowing the powertrain to operate more efficiently by optimising the power split between the two energy sources. However, complex interaction between components means realising this potential requires sophisticated control strategies to manage the torque distribution.

Dynamic programming is an optimisation technique that can find the global optimal solution for a system over time by discretising the state and control variables. It has been applied for hybrid vehicle energy management with promising results. However, most studies simplify the system dynamics or do not validate the optimal results against real driving data. Furthermore, the high computational cost makes implementing dynamic programming on an engine control unit difficult. Therefore, methodologies need to use dynamic programming with high-fidelity plant models that can be simulated quickly to develop optimal control strategies.

Allouhi (2024): Proposed optimal hybrid PV/wind/battery system to power supermarkets and electric vehicle charging in Morocco. Allouhi & Rehman (2023): Optimised PV/wind/battery system for supermarkets with EV charging in Morocco; high wind site had lowest cost of energy. Anselma et al. (2021): Validated optimal predictive energy management strategy for hybrid vehicles considering battery ageing; showed potential to downsize battery. Barman et al. (2023): Reviewed smart charging approaches for integrating renewable energy and electric vehicles. Dan & Zhou (2023): Reviewed energy integration between flexible buildings and e-mobility using demand-side management and model predictive control. Donateo et al. (2021): Optimised energy management strategy for hybrid electric helicopters using dynamic programming; reduced fuel consumption up to 22%. Er et al. (2024): Optimised rural microgrid design with PV, wind, battery, hydrogen storage, and vehicle-to-grid; hybrid storage lowered costs. Gabbar & Siddique (2023): Evaluated hybrid nuclear-renewable system for fast EV charging station; reduced emissions and costs. Gobbi et al. (2024): Reviewed traction motor design aspects to maximise electric vehicle efficiency. Hernández-Nochebuena et al. (2021): Analysed household renewable hydrogen production for fuel cell vehicles; energy storage dynamics affect feasibility. HomChaudhuri et al. (2016): Developed a hierarchical strategy for connected hybrid vehicles using traffic data; improved fuel efficiency. Itani & De Bernardinis (2023): Reviewed energy management strategies for dual-source hybrid electric vehicles. Jayakumar et al. (2022): Assessed the potential of hydrogen for sustainable mobility in India; costs need to decrease. Khalafian et al. (2024): An optimised renewable system for electricity, heat, and smart EV charging using compressed air and thermal storage. Kyriakou et al. (2024): Developed multi-agent control for microgrid with building prosumers and electric vehicles. Liu et al. (2021): Reviewed driving cycle-based energy management strategies for hybrid electric vehicles. Louback et al. (2024): Reviewed the design process for energy management systems in dual-motor electric vehicles. Ma et al. (2021): Reviewed fuel cell-battery hybrid systems for mobility and off-grid applications. Machacek et al. (2024): Analysed potential to reduce emissions in hydrogen hybrid vehicles through energy management. Manirathinam et al.

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This paper presents the modelling and optimal control of a powertrain using Matlab/Simulink and dynamic programming. The combustion engine, electric motors, battery and vehicle dynamics were modelled based on data from literature. A computational model was created and validated by comparison with experimental data from chassis dynamometer testing. This validated non-optimal model provided a basis for global optimisation using dynamic programming. Two cases were analysed – one optimised only torque distribution and the other optimised the engine operating points.

The validated plant model enables high-fidelity evaluation of control strategies prior to real implementation. Dynamic programming results demonstrate the potential for reducing fuel consumption below the non-optimal baseline. The methodology followed allows systematically developing and assessing optimal control solutions. Future work should focus on strategies optimised for real-world driving cycles using local optimisation methods that can be deployed on engine control units. The introduction of electrification in vehicles is only projected to increase; therefore, the importance of optimal energy management will continue growing.

Materials and Methods

Vehicle Architecture

The vehicle architecture modelled in this study was the Toyota Prius Generation 2, which has a series-parallel hybrid topology. This combines aspects of series and parallel configurations, allowing flexible operating modes. The powertrain consists of a 1.5L Atkinson cycle gasoline engine, two electric motor-generators, a planetary gear transmission, and a nickel-metal hydride battery pack.

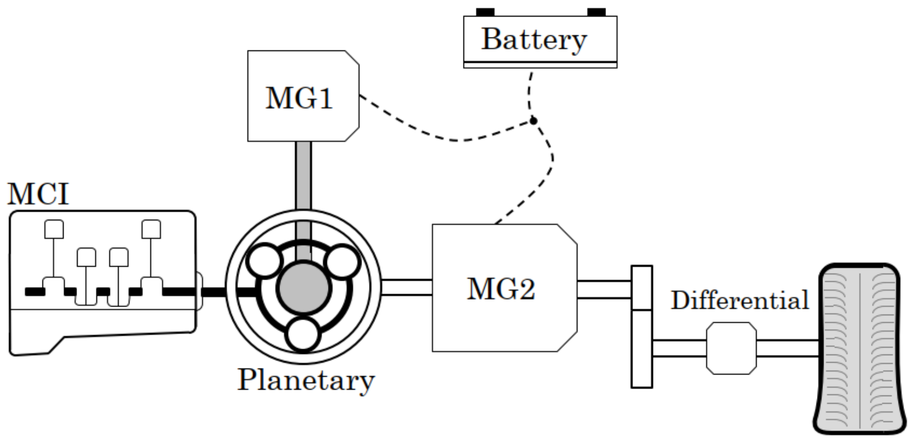

Figure 1 Illustration of the powertrain of the adopted vehicle.

The main components illustrated in figure 1 are planetary transmission, internal combustion engine (MCI), motor-generator with main power generation function (MGI motor-generator with main traction function (MG2)), and high voltage battery. The transmission system also has a speed reduction, a differential and the semi-axle connected to the wheels. The frequency inverters of each motor and the DC/DC converter are not illustrated in the figure; however, the modelling includes the losses they introduce into the system. The engine and motor-generator 1 (MG1) connect to the planetary gearset. MG1 primarily controls engine speed. Motor-generator 2 (MG2) is coupled to the gearset output and drives the wheels. The battery pack provides power to MG1 and MG2. During electric driving, the engine is off and MG2 propels the vehicle. In hybrid mode, the engine provides power to MG1 and the wheels, while MG2 supplements traction. MG2 also recovers braking energy. The planetary gearing enables a power split between engine and electric paths.

Modelling

Individual component models were developed for the engine, MG1, MG2, battery and vehicle dynamics. Using a brake-specific fuel consumption map, the engine model calculates fuel consumption based on speed and torque. MG1 and MG2 use efficiency maps to determine electrical power from mechanical power. The battery model simulates open-circuit voltage and internal resistance. Vehicle longitudinal dynamics were modelled accounting for tractive force, drag, rolling resistance and inertia.

The component models were implemented in Matlab/Simulink. The closed-loop system is simulated by combining the models with a driver model that follows the target speed profile. Restrictions on state and control variables are included. The cost function for optimisation is total fuel consumption.

Control Strategy

A rules-based control strategy approximating the logic in the Prius was developed. The engine on/off threshold and operating line were set based on analysis of experimental data. The torque distribution between the engine and MG2 was controlled based on power demand and battery state of charge.

Optimisation

Dynamic programming discretises the state and control variables to find the global optimal trajectory over a drive cycle. It was implemented using the Snopt optimal control software. Two cases were run – one optimising just torque distribution and another also optimising engine operation. Restrictions on battery charge and component limits were included. The cost function was total fuel consumption.

2. Experimental Setup and Procedure

Experimental data for validating the model and analysing the stock Prius control strategy was obtained from testing conducted by Argonne National Laboratory using a chassis dynamometer. The key elements of the experimental setup and test procedure were as follows:

Test Vehicle

A second-generation Toyota Prius with a 1.5L Atkinson engine, 43 kW permanent magnet MG1, 50 kW permanent magnet MG2, and 6.5 Ah nickel-metal hydride battery pack was tested. The vehicle had approximately 257,000 km total mileage at the time of testing.

Testing Equipment

The vehicle was mounted on a 48-inch single-roll electric chassis dynamometer capable of simulating inertial loads. The test cell temperature was maintained at 25°C. Emissions measurement instrumentation included Horiba THC, CO, CO_2, and NO_x analysers. Fuel consumption was measured using a fuel flow meter and balance scale. Additional sensors recorded battery current, engine speed, vehicle speed, and accelerator pedal position. Data was collected via the vehicle CAN bus and a dedicated data acquisition system.

Test Cycle

The urban Brazilian NBR6601 drive cycle was used for validation tests. It is an ECE-15-derived cycle with a total duration of 589 seconds and a distance of 2.09 km. Maximum speed is 58 km/h with an average 18.7 km/h. Accelerations reach 1.04 m/s^2. This cycle represents city driving conditions.

Test Procedure

Prior to testing, the vehicle battery state of charge was adjusted to 60% to represent a partially depleted condition. The dynamometer load setting was configured to reproduce road load forces for the vehicle weight. The vehicle was then driven over consecutive NBR6601 cycles with data logged for each cycle. Emissions sampling occurred during the fourth cycle with vehicle preconditioning occurring over the first three cycles. Between cycles, the vehicle was allowed to regen the battery through coast down to maintain repeatable initial conditions.

In total, the vehicle completed four full cycles.

This section presents the validation of the closed-loop simulation of the vehicle control and blueprint. The primary objective of validation was to achieve a computational model in which the estimated fuel consumption presented a deviation of no more than 5% compared to test data.

The data used for validation were obtained from Argonne National Laboratory (2013), which conducted tests with the Toyota Prius vehicle on a chassis dynamometer. The experiment was conducted under the urban area cycle specified in the Brazilian standard NBR 6601, which regulates the measurement of emissions in light motor vehicles. Details of this cycle are provided in APPENDIX C. The measured data included signals from the vehicle's CAN network and the dynamometer control system.

Data Analysis

The primary data analysed were fuel consumption, battery current, battery state of charge, and engine speed. Total fuel consumption was determined by the difference in fuel tank mass before and after the test. The integrated fuel flow over the fourth cycle provided cycle-specific consumption. Battery current and engine speed profiles were used to validate the model. Comparing the initial and final battery states of charge assessed the charge balance. Additional data provided insights into the stock control strategy.

This chassis dynamometer test provided experimental data from a real-world drive cycle under controlled, repeatable conditions. The resulting vehicle operating parameters and fuel consumption comprise a comprehensive data set for validating the Prius plant model developed in this research. The test methods follow industry standard practices.

3. Results and Discussion

Model Validation

The simulated speed profile accurately tracked the target cycle with minimal control error.

Engine speed matched well with test data, capturing the on/off pattern and transients. Some deviation occurred during the initial warm-up where emissions strategies differ. Battery current showed similar charging and discharging behaviour. However, the modelled state of charge range was narrower than testing. This indicates differences between the modelled and actual control logic.

The simulation was conducted using the Matlab/Simulink program. A time step of 0.01s was used, and the method for solving ordinary differential equations was Dormand-Prince (RK5). The torque demand from the driving cycle is the input parameter of the simulation. It must be accurate before validating the model. Therefore, the first module to be validated was the driver model. Figure 2 shows the graphs of the vehicle's actual and desired speeds and the PID controller's performance. The NBR 6601 standard stipulates that the speed error should be no more than 1 km/h. The maximum error of the PID controller in the resulting driver model is within the range (-0.4, 0.4).

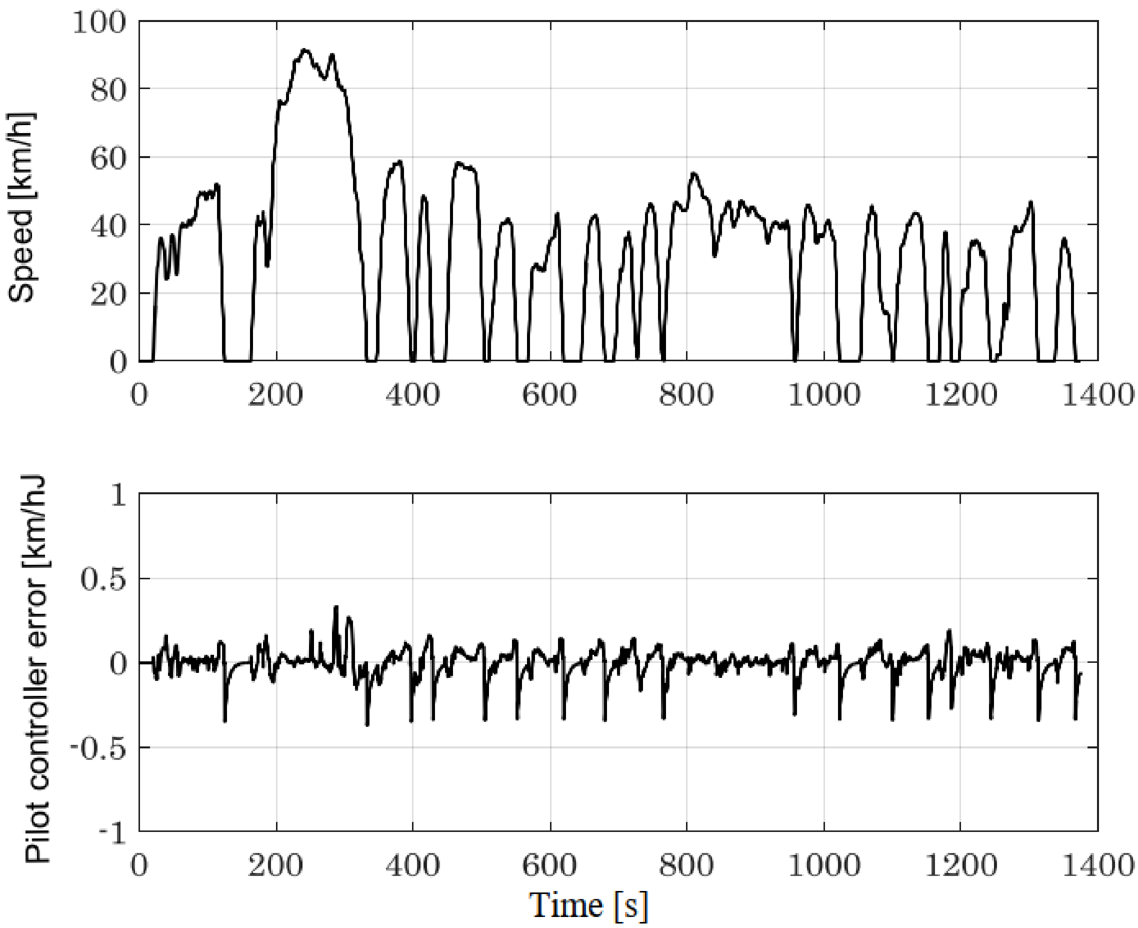

Figure 2 Vehicle speed (above) and pilot controller error (below) for the model simulation is not optimal.

In Figure 2, the simulation results and tests for the rotation of the MCI (Motor Control Interface) are presented. While the simulation indicates that the MCI employs a turn-off strategy at the start of the cycle (0 to 150 s), the test data reveal that it remains operational during this period. The MCI in the actual vehicle implements a strategy to heat the exhaust system at the beginning of the test as part of the emissions reduction strategy, a phenomenon not accounted for in the MCI model. The second graph in Figure 3 focuses on a specific section of the driving cycle. Despite instances where there is a deviation between the measured and simulated MCI rotation of 500 rpm, it is observed that, overall, the simulation closely replicates the MCI dynamics.

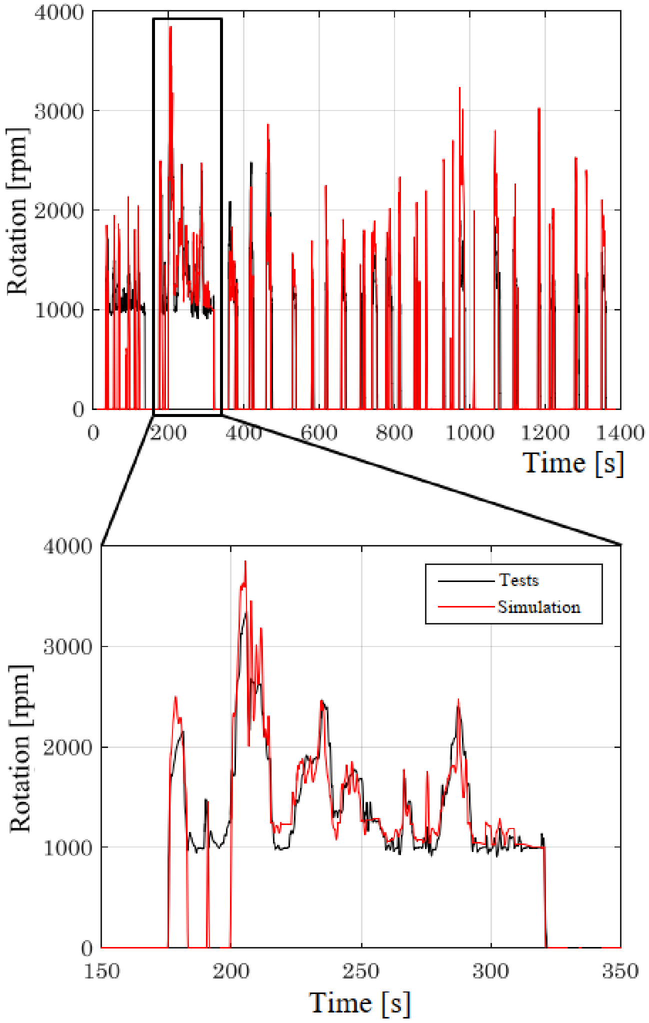

Figure 3 Comparison of the MCI rotator.for simulation of the non-optimal model wih the rotation obtained in tests

The fuel consumption for the simulated cycle was 0.377 L versus 0.373 L measured, an error of only 1.2%. This demonstrates the model accurately represents the real system efficiency and captures the interactions between components. The small state of charge error contributes minimally to fuel consumption. Additional minor discrepancies are likely attributable to unmodeled behaviors.

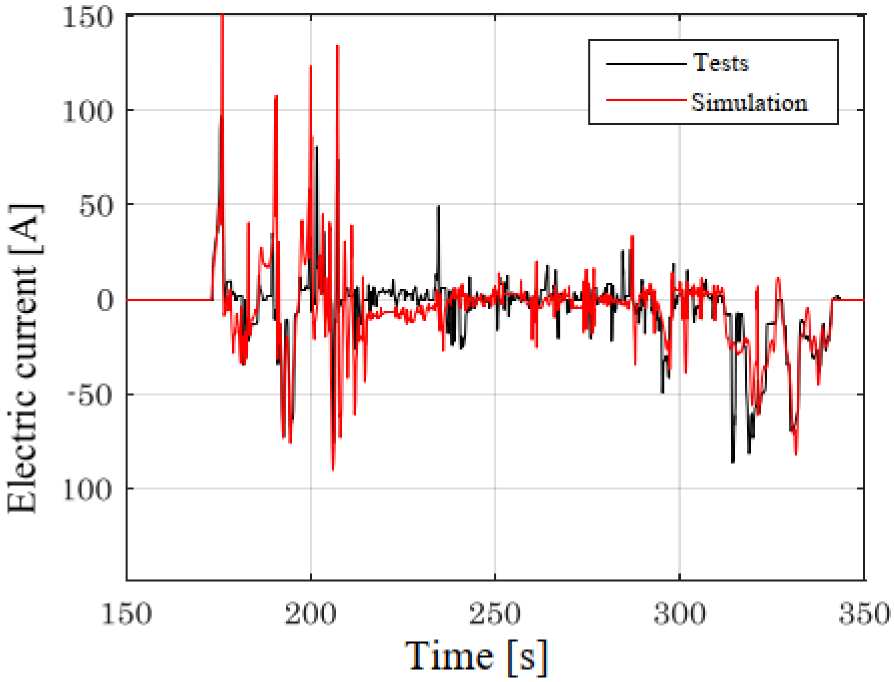

Figure 4 Comparison of the battery's electrical current for simulating the non-optimal model with the electric current

Figure 4 compares the electric current in the battery within the same visualization space as the figure above. Once again, a good overall adherence of the simulation to the test data is observed. The electric current in the battery is directly proportional to the battery power, and, therefore, the graph serves as a reliable representation of the torque distribution ratio adherence of the simulation to the actual vehicle. This comparison underscores the simulation's ability to accurately replicate the electrical behavior of the battery as observed in real-world tests conducted by Argonne National Laboratory in 2013.

Figure 5 presents the battery's State of Charge (SOC) graph over time. The initial SOC in the test was 59.2%, while it was set at 60% in the simulation. It's crucial that the SOC at the end of the cycle does not significantly differ from the SOC at the beginning to ensure that fuel consumption is not unduly influenced by electrical energy consumption. The variation in SOC observed in the experimental data and the simulation were and , respectively. This minor difference was deemed negligible, and no subsequent adjustment was made to the value of energy consumption. The figure provides a side-by-side comparison of the battery's State of Charge (SOC) and fuel consumption, showcasing the simulation's accuracy against real-world test results obtained from Argonne National Laboratory in 2013.

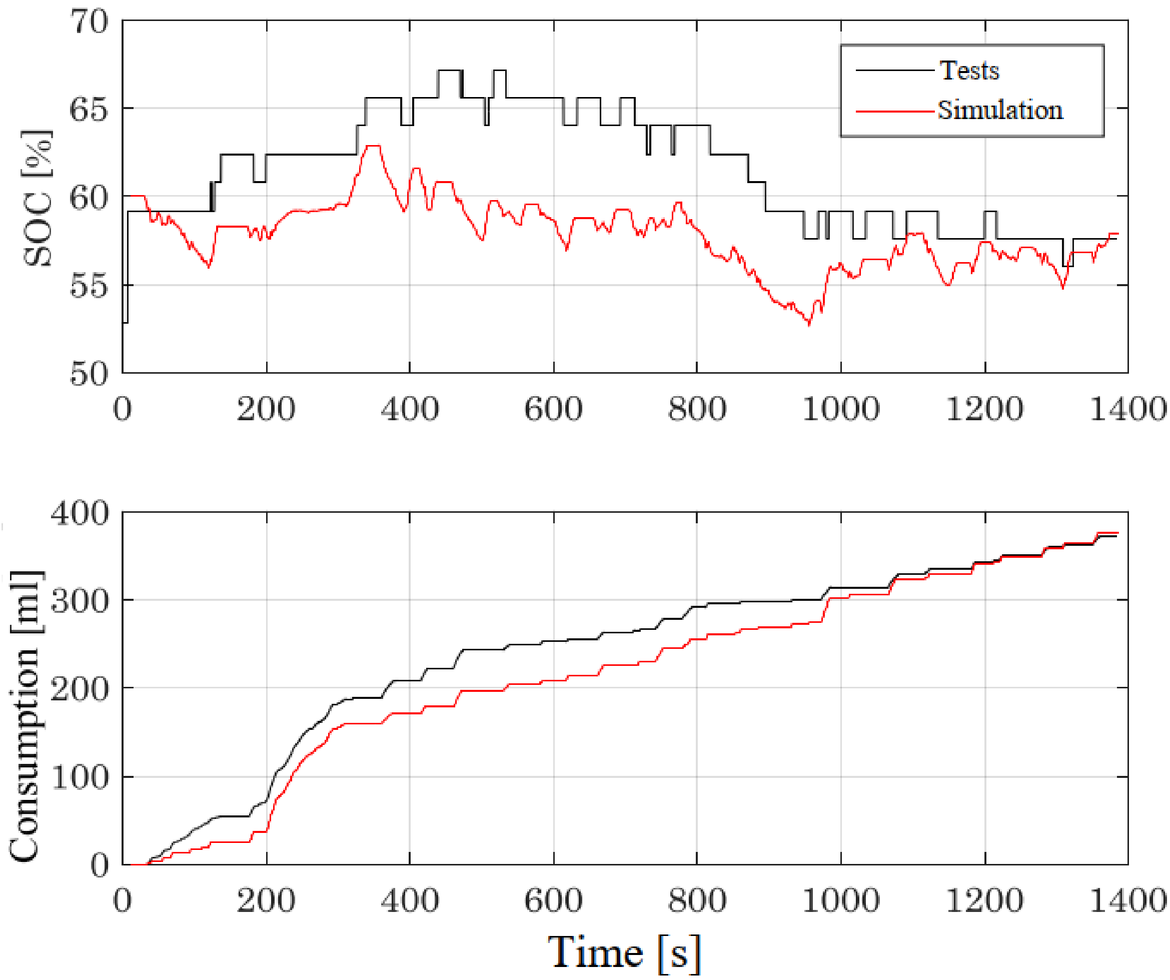

Figure 5 Comparison of battery state of charge (SOC) (above) and power consumption

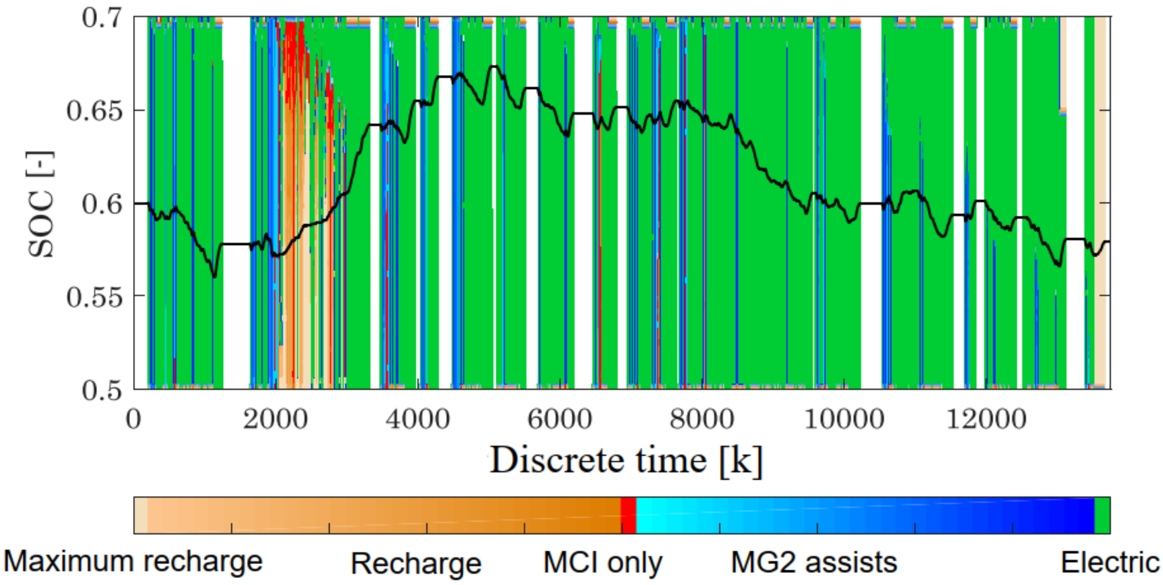

Figure 6 Result of case 1 for the battery SOC. The contour plot shows all 6optimal control solutions resulting from global optimization.

Figure 6 likely illustrates the results of a simulation or optimization process concerning the State of Charge (SOC) of a vehicle's battery (possibly an electric or hybrid vehicle) under certain operational conditions (case 1). The figure might show a trajectory or path that represents how the SOC changes over time or through different stages of vehicle operation. Accompanying this trajectory could be a contour map that visualizes the values of a control variable (denoted as \(r\) in this context) at various SOC levels. These control variable values are critical for understanding how the vehicle's control system adjusts or should adjust under different SOC conditions to optimize performance, efficiency, or other objectives. The colors and operational modes indicated in the legend, referenced as detailed in Equation (33), categorize the control strategies or states the vehicle's system adopts at different SOC levels. The interception points between the SOC trajectory and the contours of the control variable \(r\) signify the optimal control solutions determined through dynamic programming, a method often used in optimization problems to find the most efficient way to achieve a certain objective.

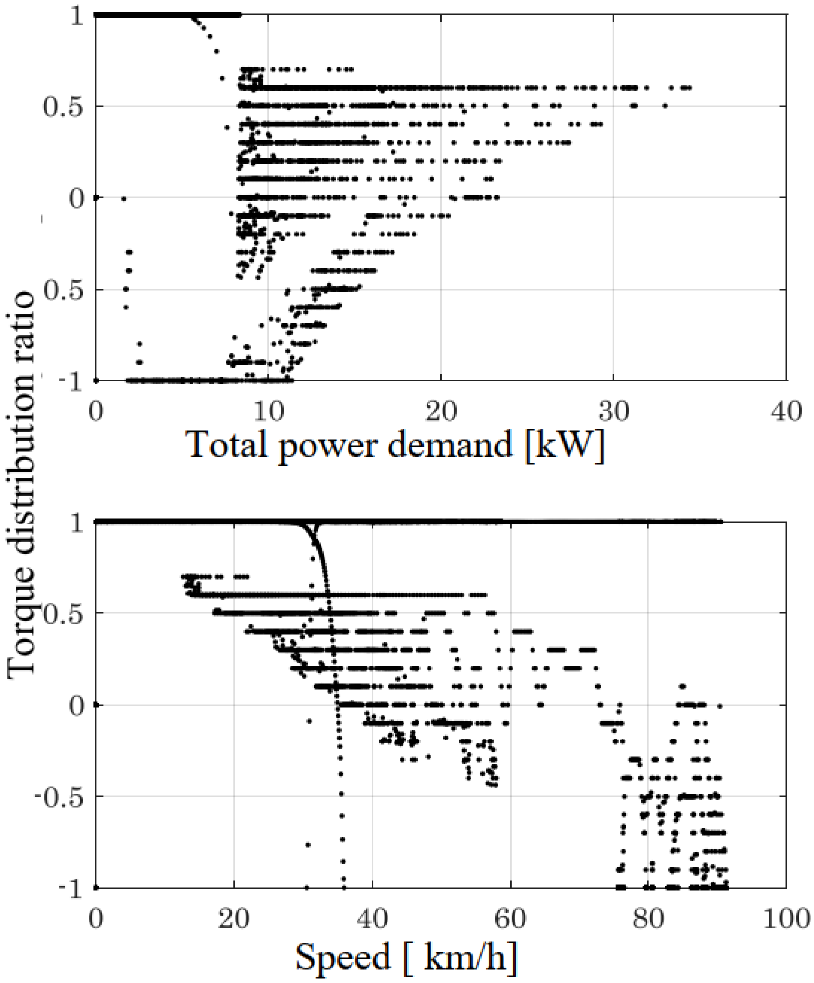

Figure 7 Torque distribution ratio as a function of power demand (above) and

Figure 7 on the other hand, explores the dynamics of the control variable concerning the vehicle's speed and the total power demand at the wheels. This figure likely presents graphical analyses or plots that elucidate how the vehicle's system's control strategies (or operating modes) vary with changes in speed and power requirements. The mention of "3 operating modes" suggests that the analysis categorizes the vehicle's performance or control responses into distinct modes based on these two parameters (speed and power demand). These modes could represent different energy-use strategies, such as electric-only operation, hybrid operation (combining electric and internal combustion engine power), and perhaps an efficiency-optimized mode that seeks to minimize fuel consumption or emissions while meeting the power demands.

Figures 6 and 7 provide visual and analytical insights into how a vehicle's control system manages its energy resources (particularly the battery's SOC) in response to various operational demands and conditions. These insights are crucial for developing and validating advanced vehicle control strategies, aiming for optimal performance, efficiency, and sustainability.

The model validation confirms that the component and vehicle system models are suitable representations of the Toyota Prius. The model has high fidelity in terms of fuel consumption, the most relevant metric for optimization. Minor control logic differences have negligible impact on total energy use over a full drive cycle. This validated model provides a robust platform for evaluating optimal control strategies.

Optimal Control

Both dynamic programming cases demonstrated substantial reductions in fuel consumption compared to the non-optimal rules-based controller. Case 1 lowered fuel use 9.5% by optimizing just torque distribution. Allowing engine operation to deviate from the optimal line in Case 2 realized an additional 1% reduction.

The results highlight that confining the engine to its optimal line does not necessarily yield the true global minimum. Other simultaneous efficiency trade-offs between components can shift the system-wide optimum. The modeling and optimization approach captured these complex interactions and revealed additional potential consumption reductions.

However, the predicted savings concern the model baseline control, not the actual Prius strategy, which likely approaches optimal already. The potential improvement on the real vehicle is likely smaller than suggested by these percentages. Additional real-world drive cycle testing could quantify possible savings.

In summary, the optimization results prove the concept of using dynamic programming to minimize fuel consumption. Even without perfectly accurate system models, the technique clearly identifies improved solutions over heuristic control strategies. Expanding the methodology to multipoint local optimal solutions could enable online implementation of near-globally optimal controllers.

5 Conclusions

This research presented a methodology for developing and evaluating optimal energy management strategies for hybrid vehicles. Models of the Toyota Prius were implemented in Matlab/Simulink and validated against chassis dynamometer test data. The validated non-optimal model matched measured fuel consumption to within 1.2% over a real-world drive cycle. Dynamic programming was then applied to optimize the powertrain control globally.

The optimal control resulted in 9.5-10% lower fuel consumption than the non-optimal rules-based strategy. This demonstrates the potential for improvement over heuristic controllers. The importance of optimizing multiple degrees of freedom, not just the engine operating line, was shown. The modeling and simulation approach enabled systematic analyzing the complex system interactions and trade-offs in hybrid vehicle optimization.

However, the actual fuel consumption benefits may be less than predicted since the production Prius control is likely near-optimal already. Further validation under real-world driving conditions could provide more accurate quantification of potential savings. Additionally, the computational expense of dynamic programming currently precludes online implementation. Transitioning to multipoint local optimization methods is needed to develop controllers that could be deployed on vehicle engine control units.

This research presented a novel methodology for developing optimal hybrid vehicle energy management strategies using simulation tools. The system modeling and optimization framework can provide valuable guidance for designing control algorithms. However, experimental validation and practical implementation considerations must also be addressed in translating simulation results to real systems. The modeling and analysis approach followed lays the groundwork for achieving globally optimal energy management in hybrid vehicles.

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