A Trip Planning-Assisted Energy Management System for Connected PHEVs: Evaluation and Enhancement

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The built-in Energy Management System (EMS) of Plug-in Hybrid Electric Vehicles (PHEVs) plays an important role in the fuel efficiency of these vehicles. Recently, it has been revealed that prior knowledge of the upcoming trip can assist EMS to enhance the distribution of power between the energy sources, i.e. the engine and the motor-generators used in PHEVs, resulting in lower fuel consumptions. This dissertation intends to further investigate on a Trip Planning-assisted EMS (TP-assisted EMS), by studying its feasibility for online implementation, and evaluating its performance and robustness with respect to the trip data uncertainties in various practical scenarios, to ultimately answer this question: Does the TP-assisted EMS function as a reliable system for PHEVs which can outperform conventional methods?

This research starts with improving upon an existing Trip Planning module with an emphasis on its online integration with the EMS module. In particular, the power-balance model of PHEVs is introduced, which is computationally inexpensive and yet adequately accurate to be used for the optimizations involved in the Trip Planning module. To speed up the optimizations, the use of Particle Swarm Optimization (PSO) algorithm is suggested. These modifications result in the reduction of computational time, making TP-assisted EMS module suitable for online implementations.

Once the TP-assisted EMS module has been integrated with a high-fidelity model of the baseline PHEV, namely, 2013 Toyota Prius PHEV, its performance and sensitivity/robustness have been extensively studied through Monte Carlo simulations, where numerous samples of standard as well as real-world drive cycles have been tested. However, in order to use these data for Model-in-the-Loop (MIL) and Hardware-in-the-Loop (HIL) tests, a Micro-trip Generator block has been developed. This block automatically segments the drive cycles, similar to the way that trip information is obtained in practice, making the simulation samples compatible with the Trip Planning module.

Statistical analyses of the simulation results show that the TP-assisted EMS is a superior controller compared to the conventional EMS strategies. Moreover, these simulations present one of the first sensitivity analyses that have been performed in the context of TP-assisted EMS for PHEVs, showing that this system is robust despite the existence of random disturbances and meanwhile has low sensitivity against variations of the design parameters.

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Dedication

To Sadaf, Vida and Shahbaz.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation and Challenges

Environmental issues, energy crisis and the ever-rising fuel cost continue to remain among the major concerns around the globe. To deal with these problems, research communities have suggested various regulations, some of which enacted by governments and authorities either regionally or globally, which generally undertake one or more of the following directions: (1) reduce the fuel consumption and the emission level of the Internal Combustion Engine (ICE) driven vehicles which use high energy density oil-based fuels but suffer from low efficiency, (2) restrict transportation activities and automobile purchases, and (3) increase the use of renewable-energy-propelled vehicles. Investigating these strategies, the first one seems somewhat impractical since improvements on the fuel economy of ICEs are known to be limited. The second approach is susceptible to distress the automotive industry. The latter advocates development of green vehicles, especially electrical-energy-driven ones because they provide up to three times greater efficiency compared to ICE-propelled vehicles. Therefore, the third solution is deemed the most favorable direction to take [1, 2, 3].

As a result, automotive industry has been enforced to promote the usage of green vehicles, including electric vehicles (EVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs). It is envisioned that by increasing use of these vehicles, the annual fuel consumptions and the CO2 emissions will significantly reduce in near future so that the strict standards of the American Corporate Average Fuel Economy (ACAFE) will be complied in a certain timeline.

Nevertheless, the initial price and maintenance cost of the electrically-propelled vehicles make them less appealing compared to their ICE-based counterpart. It is presently believed that by improving the fuel-economy and overall performance of electric vehicles, the greater long-term operational benefits of these vehicles will attract more customers which will lead to reduction of fossil fuel consumption and emission rates. Along with this line of thought, while there is an essential need for technological advances on the vehicles' powertrain components, there is a more important need to develop efficient control strategies that optimizes the operation of the state-of-the-art of technology.

Among the three types of electrically-propelled vehicles, EVs rely solely on the electric energy obtained from the external grid and charged into a battery. The vehicle electrification reduces the CO2 emissions as well as preserves the non-renewable oil-based resources since the electricity can be produced from renewable and cleaner energy resources. This makes EVs an ideal substitute for ICE-based vehicles; however, their low operating range coverage (up to 400km) and expensive costs hinders their extensive commercialization.

On the contrary, being accompanied by an ICE, HEVs and PHEVs can extend the operating range, and at the same time enhance the efficiency levels. However, PHEV is a more viable and sustainable choice because its battery's operating range is much wider than the one of a HEV. A PHEV is nothing but a HEV with the added ability of substituting electricity from the grid, unlike conventional HEVs that only rely on gasoline. This reduces the demand for a powerful ICE in PHEV, thus leaving more space for the electrical powertrain. As a result, PHEVs provide a higher fuel efficiency and lower emission compared to HEVs. This higher efficiency of PHEVs is greatly reliant on the energy management strategy that defines the power split ratio between the engine and the battery.

HEVs energy management algorithms are typically use pre-planned optimized maps, rule-based methods, or instantaneous optimizations in order to minimize fuel consumption while maintaining the battery state of charge (SOC) within the acceptable range [4, 5]. The instantaneous optimization-based methods require the current vehicles states such as demanded power and the battery SOC as well as the driving conditions such as the current vehicle's speed. Instantaneous optimization methods are implemented as the core of Equivalent Consumption Minimization Strategies (ECMSs) which first developed by [6] in an attempt to obtain power distribution ratio. In HEVs energy management systems, there is a strict constraint on the battery's SOC to operate within an acceptable limited range for the entire trip; whereas, in the PHEVs, the SOC operating range is relatively larger.

The potentials of PHEVs cannot fully be exploited by using exactly the same methodologies used for HEVs: the PHEV's charge depleting characteristic brings significant complexity to the energy management problems. In fact, the battery's SOC is known as a critical state in determining the power distribution between engine and the electric drive. A PHEV can be run in its charge depleting (CD) mode until it gets to the minimum allowable battery SOC level; then it goes on the charge-sustaining (CS) mode trying to maintain the SOC level at its minimum value just like an HEV [7, 8]. This CDCS mode is known to be sub-optimal for the trips with longer lengths than the all-electric-coverable distance [9]. On the other hand, it is proved that the blended strategy, which balances the use of engine and the battery for the entire trip for the battery to get depleted to the lowest acceptable value by the end of the trip, can capture the PHEV's maximum energy economy [8]. The blended-based strategies, however, require future trip data to obtain a near-optimal solution for the energy management problem [10, 11].

The look-ahead trip can be estimated either: (a) online by using traffic monitoring systems such as cameras and sensors alongside other technologies such as Global Positioning System (GPS), Intelligent Transportation System (ITS), and Internet maps; or (b) offline by employing some machine learning methods or Markov process over the historical driving information. Due to the driving's stochastic nature, acquiring exact future itinerary knowledge is almost unfeasible; however, most, if not all, real-time energy management systems (EMSs) in the literature neglect the non-deterministic features of the traffic prediction, despite the fact that the external prediction sources are certainly imposing some uncertainties on the systems including the errors, delays and noises as a matter of mis-communication and detection limits. Hence, it is essential to analyze the controllers' performance under the prediction's uncertainties with respect to different scenarios. If the controller is proved to be sensitive to the stochastic nature of the prediction, some modifications can be implemented in the algorithms or the EMS architecture to handle the uncertainties and improve the robustness [12, 13].

Energy management systems have been extensively studied in the existing literature and it has been revealed that the adaptive ECMS (A-ECMS) and the Model Predictive Control (MPC) are superior among others, which can also benefit from incorporation of future trip prediction while operating [14]. Furthermore, the hierarchical systems consisting of more than one module are demonstrated to be even more efficient [15, 9, 16, 17]. In this particular type of EMS, a supervisory module is usually designed to specifically generate the SOC reference. This element is provided with the trip information prediction by a preceding module. Typically, trip information can be integrated in the prediction-derived EMSs in any of the following ways depending on the algorithms used within the modules: (1) offline short-range prediction such as the stochastic forecasting that is used within a stochastic MPC (SMPC) approach; (2) offline long-range prediction that can be implemented within some stochastic approaches like stochastic dynamic programming (SDP);

(3) online short-range prediction like what is used within a MPC algorithm; (4) online long-range prediction such as the one which is employed by dynamic programming (DP) optimization mostly for obtaining the preplanned driving tasks; and (5) a combination of two of the above-mentioned scenarios within a hierarchical EMS which is usually formulated with deploying at least one online algorithm mostly as the main module for the real-time power allocation between the energy sources, and a long-term prediction-based algorithm within the supervisory module for pre-planning the power distribution according to the long-term trip information through determination of the optimum SOC profile. The optimum SOC profile is then used within the main energy management module for real-time power distribution between the battery and the engine. Depending on the algorithm, the optimum SOC profile can help update an equivalency factor for adaptive-based EMSs like A-ECMS or it can be used as the final SOC constraint employed in MPC [15, 9].

Each module of the hierarchical energy management systems has its own complexity and challenges in terms of computation costs, real-time implementation, and robustness with respect to the uncertainties. This fact alongside the added hierarchy feature makes this particular EMS a challenging problem with regard to the system's design, real-time employment, modules' effects on each other as well as on the overall EMS's performance, the error propagation in the system, and the controllers' evaluation. This thesis will investigate these challenges by incorporating different modules into a hierarchical energy management system, and then, evaluating its performance under different stochastic scenarios through an extensive sensitivity analysis under model/prediction uncertainties.

1.2 Research Objectives

Since multiple energy sources are being used concurrently within a PHEV, energy management has become an important task to determine how to best use the available resources to achieve optimal fuel efficiency. In [14], it has been reported that using the information of the upcoming trip, leads to a better distribution of power between the engine and motor-generators. By the recent technological advances, the cost of implementing accurate sensors such as GPS, V2V, radar systems, etc. has been reduced, facilitating the possibility of online trip data acquisition in vehicles. Therefore, it can be inferred that the use of future trip data can be an effective way to increase the fuel efficiency of PHEVs in near future.

However, the results of [14] on the idea of using trip prediction for energy management are preliminary, in a sense that that trip information has been used in an offline optimization procedure but in a reasonable period, and only a few sample of drive cycles have been examined. Therefore, there is currently a key gap in the knowledge of feasibility of such optimization process to be implemented in an online system. Moreover, it is not clear how such a strategy can be online integrated with the EMS, how the overall setup compares to the state-of-the-art EMS techniques, and how it will perform in real-world driving conditions where stochastic disturbances and uncertainties are inevitable. Motivated by these facts, this research has the following objectives:

- Online implementation: Study the integration with the EMS, evaluate the feasibility of the overall system for online setup and introduce modifications to reduce the computation time, if needed
- Performance analysis: Examine the performance against numerous real-world scenarios and compare to the conventional energy management techniques
- Sensitivity/robustness analysis: Evaluate the effects of trip data uncertainties and disturbances as well as the effect of variation in design parameters

To achieve the above objectives, a real-time 3-level hierarchical Trip Planning-assiseted EMS is considered in this research, evaluated for a 2013 Toyota Prius PHEV through extensive Monte Carlo simulations, where the input samples are collected from standard and real-world drive cycles.

1.3 Document Organization

This rest of this dissertation is organized as follows: Chapter 2 reviews the state-of-the-art results on HEVs and PHEVs with an emphasis on energy management and sensitivity analysis of trip data. Chapter 3 presents the architecture of the energy management module proposed for online implementations. Chapter 4 investigates the idea of using soft-computing techniques for modeling of the energy consumption. Chapter 5 is devoted to the sensitivity analysis. Finally, the concluding remarks and suggestions for future work are given in Chapter 6.

Chapter 2

Literature Review

2.1 Energy Management Systems

The fuel economy and the vehicle's performance are highly reliant on the energy management strategy to optimally divide the demanded energy between energy sources. Energy management strategies can be mathematically divided into two major categories: rule-based, causal, and nonpredictive methods; and optimization-based, acausal, and predictive approaches [1, 2, 18, 19]. Rule-based methods, also called heuristic strategies, act upon a set of rules or pre-defined maps which can usually be simply applied. Preceding trip information is not employed and the decision makings are based on the current conditions; therefore, they usually do not yield the optimal solution for many scenarios. On the other hand, optimization-based methods rely on optimizing a cost function including the energy consumption. Unlike the rule-based methods, prior driving condition is required within most of the algorithms in this category; hence, some resources call them route-based methods [14]. Each category has its own shortcomings and benefits as the rule-based approaches are less computationally expensive, but they cannot achieve the global solution; on the contrary, the optimization-based methods can lead to near-to-optimal solutions, but they are computationally expensive.

A recent work by Padmarajan et al. [19] has claimed to develop a blended rule-based EMS as a rule-based acausal EMS for the first time which, unlike any other acausal EMS developed so far, does not need any future trip knowledge; instead, known driving data and specific energy matrix are employed. The proposed EMS has been evaluated against the conventional well-tuned rule-based energy management strategy over many real-world driving scenarios considering the trip uncertainties. Engine operating modes have been preset in both approaches, but engine operation duration has been defined by the approximated energy consumption (delta energy) in the proposed method .Applying the proposed method has led to the fuel saving improvement up to 18.4% and a nine-time decrease in the number of engine on-offs compared to the conventional rule-based EMS.

Some other methods such as reinforcement learning-based (RL-based) approaches can be placed into a separate category between the rule-based methods and the optimization-based methods to balance the trade-off between optimality and real-time implementation which has recently attracted a great deal of attention from the researchers [20]. The idea of using reinforcement learning within the energy management of PHEV was initially proposed by Liu et al. [21]. The future energy usage which is dependent on the remaining travel distance is the quantity that the controller aims to learn and optimize during the trip. It has been concluded that this type of controller can overtake the rule-based controller with respect to a defined reward function; whereas, it can get worse if it does not reflect the charging opportunity. In a recent work by Xuewei et al. [20, 18], a new model-free RL-based method for PHEV EMS has been applied and evaluated which gives the benefit of being able to control the power-split operations in real time, and at the same time, learn the optimal control decisions based on the past driving conditions. It has been proved that for a given real-world drive cycle, the proposed EMS can result in a 12% fuel saving without considering the charging stations, and an 8% fuel saving with considering the charging stations. Lin et al. [22] have demonstrated a machine learning-based EMS for HEVs to minimize the total energy cost. A nested learning algorithm is applied to learn both the optimal decisions and the SOC range limitations. The inner-loop learning is in charge of the fuel consumption minimization, while the outer one accounts for the paid off battery replacement cost. Simulation results have shown that the proposed method can reduce the operating cost up to 48%.

Optimal EMSs are challenging in terms of real-time implementation since incorporating the future driving information in the optimization problem adds to the problem's complexity. Optimization-based HEV/PHEV EMSs have been investigated considerably by researches [23, 2, 1]. Different optimal control methods such as DP, Stochastic DP (SDP), Pontryagin's Minimum Principle (PMP), Model Predictive Control (MPC), Stochastic MPC (SPC), and Adaptive-ECMS (A-ECMS) have been implemented to boost the EMS. Incorporating the trip information into the EMS to decrease the fuel consumption and increase the powertrain's efficiency has been the center of attention for the last two decades [24, 25]. It has been shown that future trip information integrated with the route-based EMS can improve the fuel consumption almost 2% to 4% for certain cases [26, 27]. Moreover, it has been demonstrated that the controllers' efficiency rely on the amount of future information it is provided with [28, 14]; longer prediction window results in higher fuel economy. The future driving data can be fed into the controllers in both forms of short-term and long-term predictions depending on the controllers' algorithms and their needs. Specifically, the strategies can be divided into two main groups: 1) long-term prediction-based algorithms which need the entire trip prediction. Typically, these algorithms include the global optimization methods such as DP and PMP which can yield the global optimum solution, but they require the exact full knowledge of the future driving cycle, and therefore, they seem impractical for real-time implementation; and 2) short-term prediction-based algorithms which take into account the near future driving cycle over a defined short prediction horizon, and therefore, they are better options for online implementation; on the other hand, they cannot yield the global optimal solution.

Particularly, real-time implementable algorithms seem more attractive to the automotive researches as they are much more practical options in the real-world scenarios. However, their potentials can be further exploited if they can be accompanied by other stochastic or global algorithms, so the resultant controller is able to capture more information, while it is still real-time implementable. This idea has led to many hierarchical energy management structures with more than one real-time control module. Typically, the long-term information is integrated within a preceding module as a supervisory controller, and the short-term prediction is used within a low-level controller.

The rest of this section is organized as follows: first, a quick review on the literature of the well-established optimal control algorithms is presented; second, the literature regarding the prediction translator module which can be called "trip planning module" is investigated; then, some of the hierarchical EMSs which have been developed so far are studied.

2.1.1 Optimization-based Algorithms

Dynamic Programming

The DP is a well-established method among the global dynamic optimization methods. It requires the full knowledge of the future drive cycle to find the global solution of energy management which makes it almost impossible for real-time application especially for complex systems due to the computational burden it adds to the system. However, different actions have been taken into account to take advantage of their optimality and compensate their deficiency in terms of online implementation. One way is to reduce the model complexity by considering reasonable assumptions such as the cluster-based optimization algorithm proposed in [14]. Another way is to apply a global optimization method offline, and then, tabulate the results in a look-up table for the online decision making use. DP global minimum results have been utilized to find the near-optimal control rules for the parallel HEVs EMS. Having applied this method, the authors were able to significantly improve the fuel economy by finding the optimal energy distribution between the engine and the battery [29, 30].

Different PHEV energy management approaches during the CD mode including all-electric range and blended methods have been investigated with respect to the future trip information level [31]. The authors have shown that in the case of being equipped with the larger, and consequently, more expensive electric components, all-electric-range implementation can take advantage of all the luxuries of a full electric vehicle. On the other hand, it has been proved that the engine-dominant blended mode can result in significant fuel saving for long distance driving. In [32] it has been stated that optimum battery SOC profiles for an optimal EMS are the ones that maintain the electrical energy for the entire trip.

Stochastic Dynamic Programming

In the SDP method, the optimization is done based on the stochastic information generating from the probabilistic distribution of the driving conditions [33, 34, 35, 36]. In [34] predicted energy demand has been calculated based on the stochastic information to establish the PHEV's EMS. In the other work [35], SDP has been utilized to optimize the cost function including both fuel consumption and the battery maintenance. It has been shown that while the battery resistance growth is high at the first part of the trip, the battery is depleted quickly; afterwards when the SOC is low, blended mode is more effective.

Pontryagin's Minimum Principle

As one of the global optimal control methods, PMP finds the global solution by the Hamiltonian minimization. The performance index can be minimized in the presence of the states and input constraints. PMP method has been used in a real-time EMS of a series HEV [37, 38]. Tuning has been by considering only cruise time and regenerative energy not the entire drive cycle. Furthermore, the problem complexity has been lessened by minimizing the instantaneous Hamiltonian instead of the integral cost, which makes the algorithm real-time implementable. Using a high-fidelity HEV model in MapleSim, the authors have evaluated the controller, and then, it has been expressed that the approach results in considerable fuel saving. In another research by Ebbesen et al. [39], the firstly claimed state-of-health model for Li-ion batteries has been developed by considering the battery life in the parallel HEV EMS and using the PMP method. In order to reduce the problem complexity raised by electrochemical models, the authors have presumed that the battery's energy capacity is equivalent to the remaining cycles.

Onari et al. [40] have used an Adaptive PMP (A-PMP) in the online EMS of the plug-in hybrid GM Chevrolet Volt. Being provided with the trip distance and the average drive cycle velocity, the controller adapts its parameters based on the SOC feedback. Then, the controller has been compared against the PMP method and the CD/CS strategy which is currently used on board in the vehicle. The simulation results have shown more than 20% improvement in the fuel consumption using the proposed A-PMP.

Equivalent Consumption Minimization Strategy (ECMS)

ECMSs are among the most commonly used optimal control approaches for EMSs. It takes advantage of minimizing total energy usage including both fuel consumption and electrical energy usage [41, 42, 43, 44, 45, 6, 46, 47, 11, 48]. Basically, these two types of energy consumption are not analogous to each other by their natures; therefore, the ECMS uses an equivalency factor to direct them together in the minimization equation. Two different approaches including blended and CD methods, have been used within an ECMS by Tulpule et al. [49] for both series and parallel PHEVs. In another work [50], A-ECMS has been implemented for parallel HEVs based on the driving conditions that can calculate the equivalency factor in the ECMS. A-ECMS has been employed for power-split PHEVs [51]. Among the hybrid powertrain configuration for PHEVs, power-split architecture exploits specific benefits as it enables the engine to work at its highest efficiency by decoupling the engine crankshaft from the road and letting the electric motors to set the engine operating mode at the optimum. In [52], it has been demonstrated that near-optimal solution can be obtained by considering battery SOC depletion as a linear function of the driving distance. Partial prior knowledge has been applied in terms of distance, and the future velocity trajectory has not been taken into account.

As a new supervisory EMS controller for all types of PHEVs architecture, a general ECMS formulation has been used to find the minimum global CO2 emissions, including both direct and indirectly generated emissions [53]. Then, the PMP method has been implemented to convert the global problem formulation into local or instantaneous Hamiltonian minimization problem which takes significantly less computational effort, so the power can be optimally divided between the engine and the motor-generators in real time.

Model Predictive Control

As one of the very popular optimal control methods, model predictive control (MPC) is able to handle constrained multi-input multi-output problems [54]. This enables taking advantage of the potential of the state-of-the-art theories while taking into account the automotive industry needs. MPC has been significantly employed in the HEV/PHEV EMSs. MPC has been used for real-time control of different types of hybrid architectures [55]. In [56], the MPC has been utilized for a parallel HEV EMS to find the optimal torque distribution. In another work by Borhan [57, 58] for a power split HEV, the MPC has been employed by considering a control-oriented model inside the controller. In this work, rule-based controller, linearized MPC, and nonlinear MPC have been implemented and their results have been compared against each other. It has been demonstrated that the nonlinear MPC can lead to significant fuel savings among others. In [59], MPC has been employed for a power-split PHEV EMS, and the results have been compared against the implemented DP as the benchmark. In a recent work by Taghavipour et al. [60], the MPC-based EMS has been integrated to the high-fidelity model of a power-split PHEV developed in MapleSim. The simulation results have expressed good improvement in fuel saving.

Di Cairano et al. [61] have proposed a stochastic MPC with the driver-behavior learning (SMPCL) for HEVs EMS. It takes into account the online learning of a Markov chain of the driver's decisions along with a stochastic scenario-based optimization method and quadratic programming. Simulation results for both standard and real-world drive cycles have proved that the proposed SMPCL outperforms original MPC; indeed, the results have shown close agreement with the results of a MPC with the full prior trip information.

2.1.2 Trip Planning

Future driving conditions can be incorporated into different parts of the powertrain control systems to improve the vehicle's overall efficiency and energy consumption. In this section, it is aimed to investigate various numbers of studies that have integrated future trip information into the controllers in different ways. Depending on the type and application of the controllers, each may need a short-horizon or a long-term trip prediction. Some algorithms need exact prior knowledge of the trip; others, on the other hand, need approximate prediction. However, fully deterministic forecasted trip knowledge is not simply obtainable according to the uncertainties involved with driving. Only partial information can be acquired through the recent advancements in the navigation systems such as the geographical information systems (GISs), intelligent transportation systems (ITSs) and global positioning systems (GPSs). Also communications systems such as radars, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity systems along with the on-board sensors and the potential capability of connecting to the cloud computing sources can significantly help access to the future trip information. The partial available information is too unrefined to be incorporated to the algorithms at once, and it needs to be processed to be appropriately suitable as either short-term or long-term trip prediction. Accordingly, many algorithms have been developed to process the coarse information to get the desired form of the driving conditions. These methodologies can be mainly classified into two main groups: a) model-based methods; and b) data-driven approaches.

Model-based methods are able to predict the future traffic conditions based on the real-time traffic simulations and the traffic flow theory. Zulkefli et al. [62] have employed inter-vehicle-communications (IVC) and vehicle-infrastructure integration (VII) for the route forecasting along with an EMS based on the PMP method for HEVs. Prior traffic information has been obtained using the Gipps' car following model and the cell-transmission-model (CTM) for the leading vehicle route prediction. Keulen et al. [63, 64, 65], have used future driving information to acquire the optimum velocity trajectory which has been then fed to the cruise controller.

Data-driven approaches can estimate the upcoming traffic information based on the current and the past driving data using either Markov process or machine learning algorithms. These methods are mostly used within the stochastic methods such as the stochastic dynamic programming (SDP) [13, 66] or stochastic model predictive control (SMPC) [61]. According to the literature, artificial neural networks (ANNs) have efficiently shown good potentials for future prediction as they are easy to implement and accurate enough for simulation purposes [67]. An artificial neural network has been used to predict the road type and the traffic congestion (RT and TC) by using the data available from GPS, ITS and GIS to increase vehicle's efficiency [68]. Similarly, statistical approaches, specifically Markov chain models, are also very popular for modeling the future driving condition. Gong et al. [69, 70] have studied two approaches for integrating the trip information with the EMS: Gas-kinetic traffic flow model and neural networks, which has been trained by using the traffic information. The first method includes different parameters which results in model complexity, while the second method is demonstrated to be accurate and simple enough for real-time implementation. In a recent study by the authors [71, 72], a Markov chain model has been applied to find the speed profile which is then used for the controller tuning and increasing the vehicle's efficiency. Sun et al. [73] have developed and compared three different speed forecasters without using any on-board device data for predictive EMSs in power-split HEVs. These predictors include exponentially varying, stochastic Markov chains and artificial neural networks (NNs). They have been compared against each other in terms of tuning sensitivity, model complexity, forecasting accuracy and fuel consumption improvement. It has been shown that NN-based method outperforms its counterparts in general.

2.2 Hierarchical Trip Planning-assisted EMSs

In a hierarchical EMS, the main real-time decision maker algorithm is accompanied by one or two preceding modules to increase the efficiency. The Trip Planning module may be added to the system for different purposes. It can be implemented to translate the coarse prediction information into some indexes that are understandable by the energy management controllers such as the optimum SOC profile which can be used as the reference for updating an equivalency factor in an A-ECMS algorithm or as the final-state constraints in the MPC algorithm. Also, it may be utilized to add some stochastic knowledge to the real-time decision making process. Typically, the supervisory module is used for updating a parameter in the case of real-time implementation; therefore, the upper level controller generally takes advantage of a simpler control-oriented/power-balance system model; along the same line, the optimal control algorithms used inside the supervisory controller need to be modified to be fast enough for online applications. These different ways of applying hierarchical systems that have been studied in the literature are elaborated in details in the remaining part of this section. Also, it is good to mention that among different hierarchical architectures, the ones with dynamic traffic feedback data have been proved to be more efficient because the controller is provided with the real-time traffic information feedback.

Keulen et al. [74] have applied optimal EMS for hybrid electric trucks by using route information. First, optimal look-ahead speed trajectory has been calculated within a trajectory builder module. Then, the optimum deceleration trajectory has been applied along with an online EMS to maximize the energy recovered during regenerative braking, which has resulted in considerable fuel consumption reduction.

In [69, 75], the future power demand has been calculated based on the trip information, then a two-scale DP method has been used as the energy management strategy to optimize the battery SOC profile by using a linear battery model. The upper level DP takes into account the approximation data of the whole trip to find the preplanned battery SOC. This optimum SOC profile is then segmentally tracked by the lower level short horizon DP which has more accurate data.

In a comparative study by Bin et al. [76], the classic DP and the two-scale DP have been compared against each other. The authors have used a regulating segment model to adjust the span of the trip segments based on the trip information. This method has reduced the computational complexity. It has been found that two-scale DP yields effective result, while it is a less computationally expensive method compared to the classic DP which is calculating the demanded power and SOC numerically.

The battery SOC profile has been optimized by using the upcoming future driving data for a power-split PHEV in [77, 78]. Using the PSAT software, a rule-based controller is applied to follow the optimum SOC. Also, the authors have utilized a different segmentation method called "receding horizon approach" to reduce the computational burden. The original path with a lot of segments has been changed to a virtual route in which only initial segments of the original path are remained, and the other remaining segments of the original path to the end of the trip are presented by an equivalent segment. DP method has been used to find the optimum SOC of each of the segments by using the first segment's SOC as a reference trajectory.

Du et al. [17] have demonstrated a trip-oriented stochastic EMS for a plug-in hybrid electric bus. At first, a segment-based stochastic Markov chain model of the trajectory is constructed by clustering the past driving information of a given trajectory into the segments with respect to the bus stops. Obtaining the segment-based stochastic model, the stochastic dynamic programing problem is then used in an offline manner. Afterwards, its outputs are translated to a 3-dimensional look-up table to be used by the online module which adopts ECMS. Afterwards, the controller has been evaluated through both model-in-the-loop and hardware-in-the-loop tests for a real-world trajectory. The results have shown that the controller can outperform both the ECMS and the rule-based controller. Also, the near-optimal results have expressed close agreement with the DP results.

Tianheng et al. [15] have proposed a supervisory controller for EMS of the PHEVs consisting of three consecutive levels with respect to the predicted power demand and the prior trip knowledge. First, the power demand is predicted using a neural network method which simplifies the forecasting by converting the entire traffic cycle into some specified statistical parameters. Next, the predicted power demand is fed to a module with a mathematical model to obtain the battery SOC reference. At the end, the SOC reference is used along with an A-ECMS to find the optimal power distribution between the engine and the motor-generators. It has been shown that the proposed model can lead to considerable improvement in terms of fuel consumption and other factors compared to its counterparts including rule-based approach and the ECMS.

Sun et al. [9] have added an upper level SOC planning module to the conventional MPC-based EMS for a power-split PHEV. The proposed EMS schematic is demonstrated in Fig. 2.1. The higher level incorporates real-time long-term speed profile along with a power balance-based model to be able to find the optimal SOC profile using DP in a real time fashion which is consistent with the traffic information update rate at every 300 s. The low level module uses the obtained optimum SOC profile as the terminal state constraint for the MPC level which applies DP at each time step to solve a constrained nonlinear energy management problem. Artificial neural networks (ANNs) are used to predict the short-term velocity profile for the receding horizon employed in the MPC. Three different cases of traffic information integration have been employed to evaluate the controller: a) no traffic data is available; b) static speed profile is fed to the controller at the beginning of the trip in the both forms of the time-dependent and the distance-dependent; and c) dynamic speed profile is fed to the controller every 300 s over the trip in the both forms of time-dependent and distance-dependent. The simulation results for a highway driving case including congestion occasions have shown that the proposed controller can attain 94%-96% fuel saving of the deterministic DP.

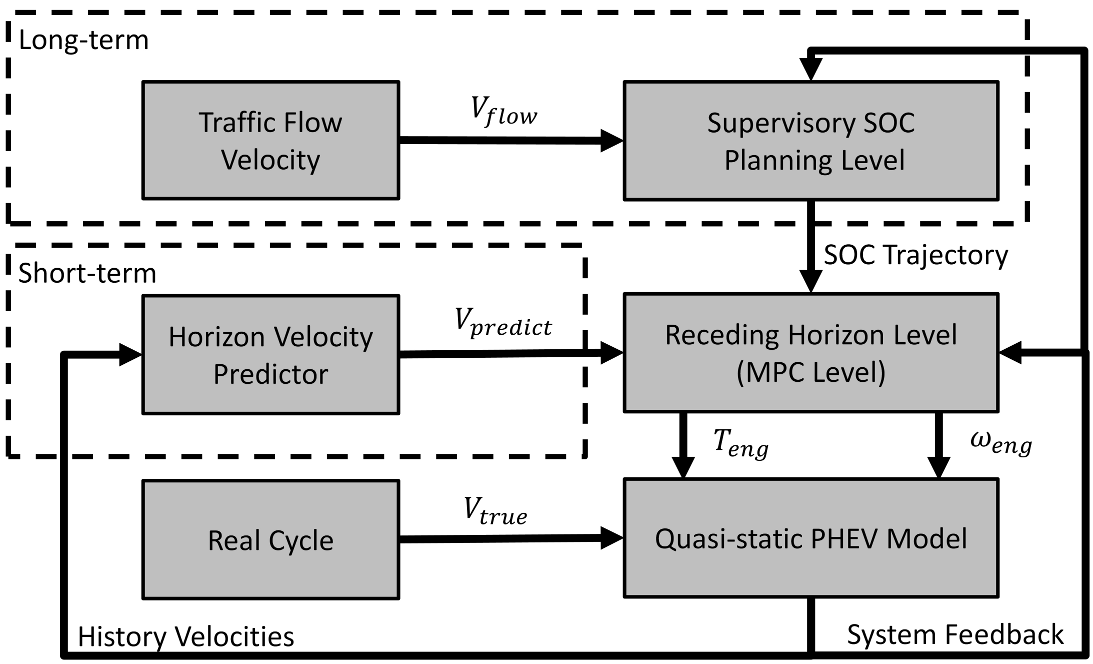

Figure 2.1: Control structure of the EMS proposed by Sun et al.

Huang et al. [79] have developed an ECMS for plug-in hybrid electric buses with a given route. Future speed profiles have been predicted using Markov chain along specific routes that are supposed to be taken by the buses. Later, an iterative learning optimization method has been applied to pre-calibrate the equivalency factor to be used by the ECMS for improving the fuel consumption which is proved to be up to 8.4% with the average of 7.3%.

In another hierarchical EMS by Jiang et al. [16], a cyber-physical two-level model has been proposed for PHEVs. This power management model is presented in Fig. 2.2. The upper level takes advantage of the real-time entire future trip prediction for the remaining part of the trip. The online battery usage policies are then obtained using multi-stage stochastic quadratic programming (MSQP). On the other hand, the low level module uses the past driving information along with the Markov Decision Process (MDP) to find the offline power split policies in the form of look-up table. Online EMS decisions are made by looking up through the extracted table using both the vehicles real-time states and the online battery SOC level. They evaluate the MSQP-MDP controller against other methods including quadratic programing MDP (QP-MDP), MDP, CDCS, and Static. The simulation results have proved that the proposed controller improves the fuel consumption compared to its mentioned counterparts.

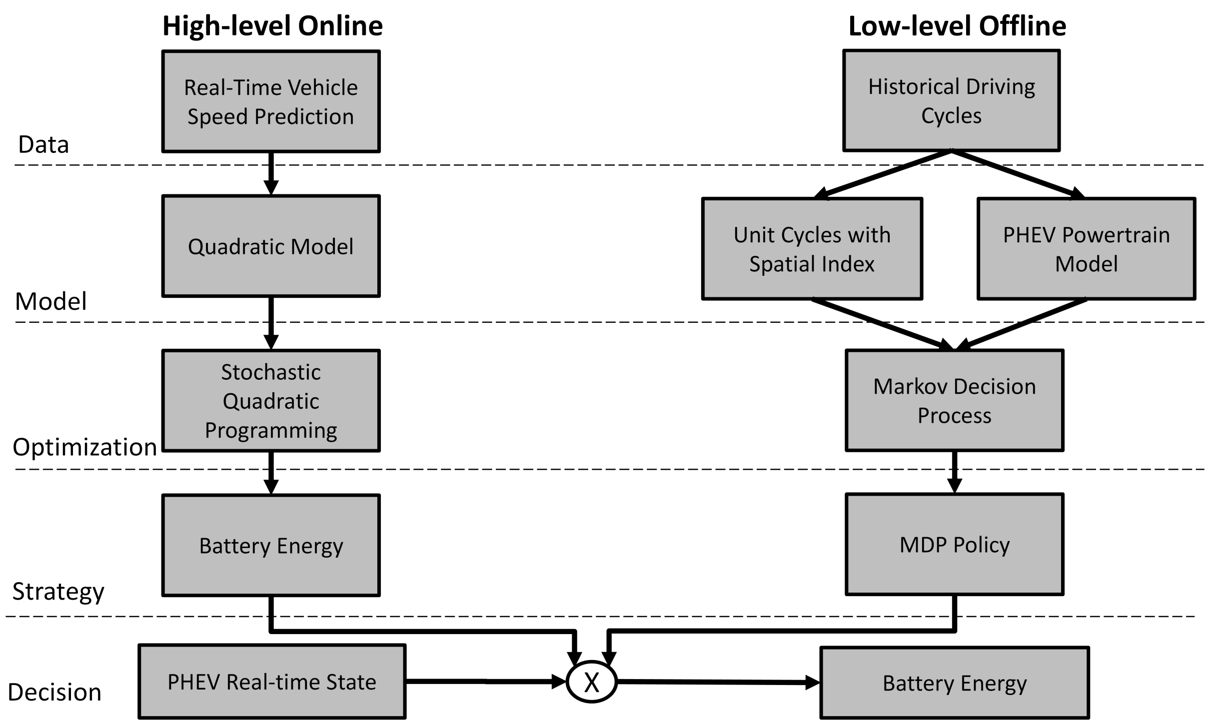

Figure 2.2: Hierarchical model introduced by Jiang et al.

2.3 Computational Intelligence

Over the past two decades, there has been a remarkable pressure on automotive industrialists to improve the quality of their products in terms of different safety and economic issues [80]. This is mainly due to the serious global regulations contrived by international associations responsible for issues such as global warming, air pollution and etc. On the other hand, automotive industrialists are trying their best to comply with economic concerns of their clients. So, automotive engineers are now seeking for some modern and efficient technologies and strategies which can assist them to further ensure the safety and convenience of passengers, and at the same time optimize the performance of vehicles in terms of fuel economy.

With this regard, there have been paramount researches to develop much more efficient components as well controlling and management tools to make sure the vehicles perform efficiently on roads [81]. The feedback of the exerted investigations have revealed that in the early 21st century, automotive engineers were mostly focused on traditional optimization, modeling and control approaches for improving the performance of vehicles. However, in so many cases, they have encountered some remarkable challenges due to the complexity of the problems and the demand for decreasing the computational complexity of the controlling and management tools to prepare them for real-time applications [82, 83]. As an example, one of the main challenging problems arising in such applications is the complexity of the resulting optimization problem at the heart of controlling and performance inspection algorithms. Usually, the resulting problems are nonlinear, non-convex and highly multimodal, with a considerable number of decision variables. This makes the applicability (or even feasibility) of traditional optimization problems very questionable. This is mainly due to the fact that most of the traditional optimization algorithms use the gradient information of the objective function (in the form of Jacobean and Hessian), and this makes them quite computationally expensive. Also, traditional / statistical identification methods such as splines and k-nearest neighbour can result in some problems such as over/under fitting, miss-approximation, etc. [84]. The same story is true for most of the classic controlling algorithms (such as proportional derivative integral and sliding mode controllers). Indeed, such controlling methods are unable to calculate the optimum controlling laws, and just care about tracking a desired trajectory [85].

Due to the abovementioned problems, automotive engineers have shown some interest to use modern methods, in particular those methods coming from the field of computational intelligence (CI). As a matter of fact, automotive engineers are not the only society who appreciate the potential of CI methods. CI is now playing a pivotal role in so many applications, and interestingly, the feedbacks of the researchers are very positive regarding their potentials [86]. Scrutinizing the success of CI for different applications is outside the scope of the current investigation. However, in what follows this section, it is intended to mention some of the most prominent and successful research activities that clearly reflect the potential of tools from CI for crucial automotive problems such as fuel consumption optimization and control.

By taking a peek into the archived literature pertaining to the application of CI to automotive problems, one can realize that the flexibility of such techniques have enabled them to be used for different types of problems, including estimation, optimization, management and control [87, 88]. In [89], a novel intelligent method was proposed which uses the mixed integer linear programming and genetic algorithm (GA) optimizer for integrated production and transportation in multiple vehicles environment. The results of the simulation indicated that the considered intelligent method can efficiently handle the considered automotive problem, and at the same time could satisfy a large number of constraints, which was not the case when using conventional techniques for the same task. In [90], a multiobjective optimization technique was developed for optimal driving during electric vehicle acceleration. The considered objective functions were the consumed energy and the acceleration duration. It was indicated that conventional optimization techniques were unable to yield a practical solution to this problem. This was due to the fact that traditional approaches used a signalized version of the objective function which combined the mentioned conflicting objectives with some weights. However, intelligent evolutionary optimizer used its heuristic power to effectively apply the notion of Pareto design to get an optimal front including non-dominated optimum solutions. In [91], a powerful nonlinear controller was derived using the fuzzy logic concept for robust steering control of autonomous vehicles. Experiments with a real prototype have endorsed the robustness of the designed controller. In [92], another powerful fuzzy controller was developed for efficient control of electric vehicles with continuously variable transmission. By comparing the results with proportional integral controller, it was observed that fuzzy can do a fascinating job for this application. In [93], an optimal intelligent load frequency controller was implemented using particle swarm optimization (PSO) and fuzzy logic and goal representation adaptive dynamic programming for optimal control of island smart grid with electric vehicles and renewable resources. In [94], a composite controller was developed based on sliding mode control and fuzzy logic for simultaneous balancing and trajectory tracking control of two-wheeled inverted pendulum vehicles. By comparing the results to traditional controller, it was observed that the intelligent technique was superior. In [95], artificial neural network (ANN) was adopted for adaptive estimation of an unmanned surface vehicle, and based on the simulation, it was demonstrated that the method was very robust to measurement noised. In [96], a support vector machine (SVM) was proposed for automatic classification of road network files for assisting the driver in unstructured areas. The results affirm the high potential of soft techniques for the considered task.

2.4 Sensitivity Analysis

Optimization-based EMSs are highly dependent on the trip prediction. According to the stochastic nature of driving cycles, a perfect prediction of future information is almost impossible; therefore, the impacts of the imperfect prediction on the EMSs must be taken into account. Nevertheless, most of the studies have assumed the prediction to be deterministic and accurate; hence, this area of research has not been deeply studied so far. This strengthens the need to consider the effect of errors associated with the trip data estimation [1, 97].

According to the current applied prediction methods, obtaining a 100% prediction accuracy is impossible [98, 99]. Some of the developed prediction techniques have up to an hour prediction window with the update rate of every 5 minutes. In [100], the prediction algorithm used for traffic speed and volume estimation has demonstrated the accuracy over 85% for a prediction window of 5 minutes up to 60 minutes. Moreover, the real travel time prediction can be used for urban driving in addition to the highway driving, for which the relative mean error has been reported to be as small as 10.8% [99].

He et al. [51, 101] have applied A-ECMS for power-split PHEVs. Furthermore, real-time implementation concerns such as the window sizes for the optimization problem and the prediction errors effects on the controller's efficiency have been discussed. The authors have considered stochastic/random drive cycles with up to 20% energy prediction errors. The acquired appropriate window size results in considerable improvement in terms of fuel savings for different driving cycles. Along the same lines, the controller has been proved to be robust in the case of inaccurate prediction; indeed, although the added error yields increase of fuel consumption, the controller still provides fuel consumption improvement compared to the benchmark controller. It is good to mention that there has not been a specific correlation detected between the error rate and the fuel savings decrease rate.

Fu et al. [102] have developed a real-time MPC-based EMS for HEVs using ITS based prediction. Then, in order to assess the effects of the speed profile prediction uncertainties on the different controllers' performance such as MPC, ECMS, and A-ECMS, a sensitivity investigation has been done with respect to the noises and errors. Real-world driving information has been utilized to estimate the speed profile for alternate real-world drive cycles. It has been demonstrated that equivalent fuel economy gain is obtained for both of the imperfect prediction and the perfect one. Simulations have not yielded similar results for different controllers as the SOC final value and the fuel economy have been reported differently, but it has been expressed that a net fuel economy is achievable by using A-ECMS and MPC. It has also been shown that appropriate speed prediction yields negligible variations in the final SOC and the fuel consumption. Also, the results help clarify the importance of future trip prediction in the real-time HEV control.

Zulkefli et al. [62] have investigated a sensitivity analysis of a PMP-based EMS for HEVs. The drive cycle's prediction error has been expressed as the root mean square value of the difference between the actual speed and the estimated speed. Both 6-mile and 15-mile cases with various forecasting update rates have been used to evaluate the controller performance against a rule-based controller. Simulation results have expressed that in the case of perfect prediction the fuel saving up to 9.6% miles-per-gallon (MPG) for the 6-mile case and 7% MPG for the 15-mile case is achievable. These benefits have been recorded to be 1.6% to 4.3% MPG for the 6-mile case and 2.6% to 3.4% MPG for the 15-mile case in the case of inaccurate prediction.

D. Asher et al. [103] have utilized one-second incremented DP over a known drive cycle to find the decision matrix for every possible state and time. Then, this decision matrix has been used to investigate real-world prediction errors and driving disturbances such as sudden traffic congestion, unpredicted signals and unplanned route change. In a later study by the authors [104], the effects of the forecasting signal uncertainties on the resultant fuel economy (FE) of the predictive EMSs for HEVs have been analyzed. To do so, two different scenarios have been considered: route type identification errors and hill planning errors. The simulation results have witnessed that the prediction-derived FE is sensitive to the prediction quality, but it has been also proved that even mis-estimated predictive controllers can outperforms the benchmark controller under different circumstances.

A sensitivity analysis on the sensor range has been investigated by Hofstetter et al. [28]. The authors have proposed a deterministic DP-based EMS for PHEVs which uses the entire route in the way that part of the trip within the prediction horizon is derived from the online sensor data; and thus, is dependent to the sensor prediction range; and the rest of the trip is roughly estimated. It is proved that the fuel economy improvement is not sensitive to the sensor range prediction as near-global optimal solution is achievable even by implementing short prediction ranges.

Karbowski et al. [105, 106] have proposed a PMP-based real-time EMS for a PHEV. According to the fact that only a rough estimation of future driving cycle can be obtained in real-world driving, a GIS-assisted stochastic trip prediction using Markov process has been used to create several uncertain drive cycles for a given route. Then, the sensitivity of the PMP tuning parameter to the driving cycle has been investigated which helps better understand the importance of having an adaptive equivalence factor to get updated as the trip goes forward.

In some other works [107, 108], the effect of different prediction factors such as traffic, road and weather on the ECMS equivalency factor has been explored. It has been witnessed that considerable fuel economy improvement is obtainable by using forecasted driving knowledge in the energy management controller.

2.5 Summary

This chapter surveys the state-of-the-art works in the area of EMS of PHEVs. It finds that the most efficient strategies suggest including prior trip information, leading to hierarchical structure for the EMS module design. The chapter covers most of the works that have been done with regards to the hierarchical EMS. Then, it follows with reviewing the sensitivity analysis works. It reveals that the integration of uncertainties with optimal energy management has not been well-addressed. In fact, there is no work done using Monte Carlo simulations and TP-assisted EMS evaluation against stochastic uncertainties that exist in real-world scenarios.

Chapter 3

Trip Planning-assisted EMS

This chapter introduces the architecture of the energy management module used in this research. This module is originally adopted from [14]; however, its computational efficiency has been refined by introducing the power-balance model and also using PSO, both for optimizations. The chapter then follows with simulation results, where the performance of the module is verified for standard drive cycles, hilly road and 60 real-world drive cycles through Model-in-the-Loop (MIL) simulations. Further, Hardware-in-the-Loop (HIL) results are presented verifying the real-time implementation capability of the module.

3.1 Energy Management Architecture

In [109], it has been reported that prior knowledge of the upcoming trip information such as speed, position, road grade, distance, position of stop sign, etc. can significantly improve the efficiency of PHEVs. With the recent technological advances in ITS, GPS, GIS and radar systems, the above-mentioned information has become easily available in real-time. Therefore, it can be expected that trip preview will become an inevitable part of energy management system of future PHEVs. Along with this line of thought, this study aimed to use future driving predictions to generate the optimum battery SOC profile and therefore achieve optimal power distribution. For this purpose, an intelligent hierarchical TP-assisted EMS is developed as shown in Fig. 3.1, where there are three main sub-modules: a Micro-trip Generator, a Trip Planning (TP), and a Route-based Energy Management System (Route-based EMS). This configuration also uses three different models, depending on the level of complexity and computational time required for a particular task. These models are:

- High-fidelity model: the most sophisticated model suitable for control evaluation and control-oriented model validation
- Control-oriented model: used in real-time control application, and
- Online optimization power-balance model: a simplified model of the power-split Prius PHEV used within the TP module.

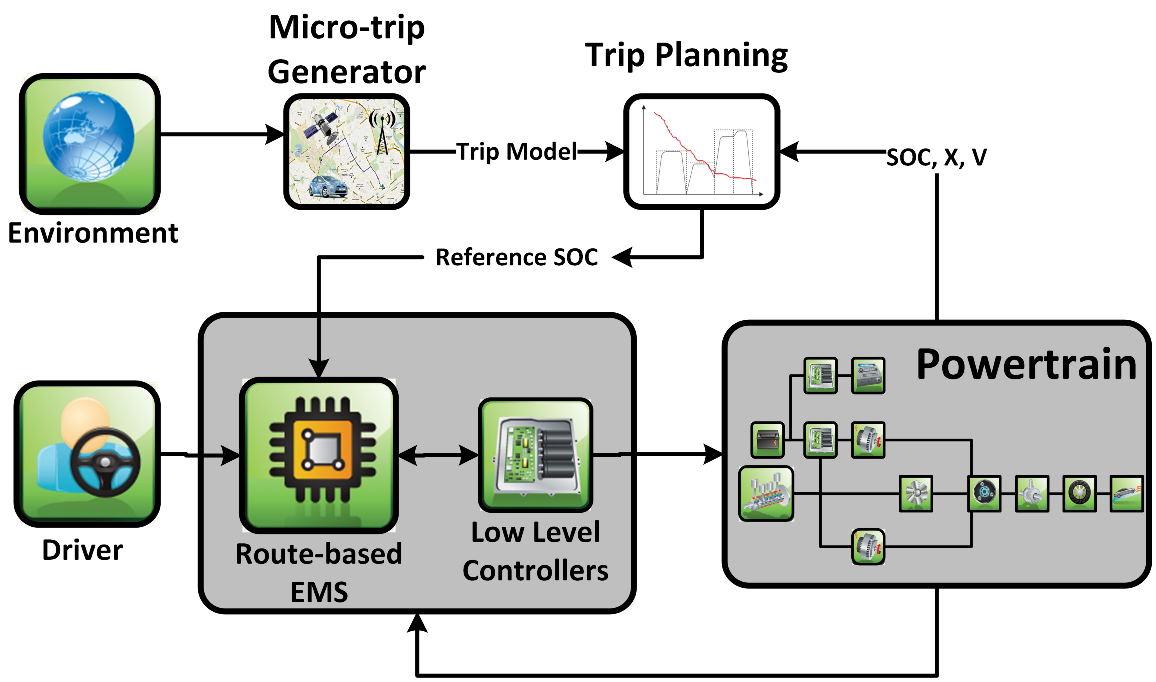

Figure 3.1: TP-assisted EMS schematic

3.2 Micro-trip Generator

Because of the stochastic nature of the driving cycles and the current limitations on traffic monitoring systems, it is impossible to make an accurate prediction of the entire trip once the trip starts. Instead, the prediction should be performed partially where only a small portion of the upcoming trip is foreseen [106]. In [63], the use of CAN bus is suggested where for every segment of the entire trip, a particular number of CAN bus messages, each carrying real-time map data of short horizons, are collected and fed into the EMS. Building on this idea, this research introduces a new module for the EMS, the Micro-trip Generator, which has the duty to automatically segment the driving cycle, both in spatial and temporal domain, in a way that the predicted trip data is compatible with the TP algorithm. This segmented trip is referred to as the trip model and each segment is known as a micro-trip which has a constant speed and road grade. The operation of Micro-trip Generator starts with the conversion of standard drive cycles, which are usually in temporal domain, into spatial data. Then, through a mathematical analysis, the speed and grade change rate over the whole drive cycle is evaluated and the entire route is divided into individual segments, each have a fixed road grad, maximum permissible speed and velocity profile. At this stage, every segment initially consists of acceleration, cruise and deceleration sections; however, they cannot be used by the trip planning algorithm because it is only compatible with the cruising speed. Therefore, the K-means algorithm is utilized in an additional step to account for the acceleration and deceleration sections and come up with a new cruise speed, which compensates for the other two sections and can be used by the trip planning algorithm. Therefore, the i^{th} segment of a trip can be uniquely identified by $[x_{initial_i},\ \Delta x_{c_i},\ \Delta t_{c_i},\ v_{c_i},\ \theta_{c_i}]^T$ where $x_{initial_i}$ is the initial location, Δx_{c_i} denotes the length, Δt_{c_i} indicates the duration, v_{c_i} is the cruise speed, and θ_{c_i} stands for the road grade of the segment and $i \in \{1, 2, ..., N_{seg}\}$ with N_{seg} being the number of remaining segments to the end of a given route. The An example of this implementation for three consecutive standard Highway Fuel Economy Test (HWFET) drive cycle, 3xHWFET, is shown in Fig. 3.2.

3.3 Trip Planning Module

The TP module receives the long-term prediction as a sequence of upcoming micro trips in the spatial domain. The schematic of TP module is shown in Fig. 3.3. It uses the real-time cluster-based optimization (RCO) algorithm adopted from [14] to minimize the total energy cost of both electrical and fuel subject to the constraints on different components of the powertrain. This module calculates the fuel consumption and ΔSOC of each segment and then produces the optimum SOC profile for the predicted drive cycle over the entire trip, which will be then fed into the Route-based EMS module. With this design, the TP module produces regular updates along the trip, provides up-to-date optimum SOC profile for the Route-based EMS and ultimately results in a better efficiency.

Since the above calculations are required to be performed online, the computational efficiency becomes important. To address this concern, this work uses a simplified power-

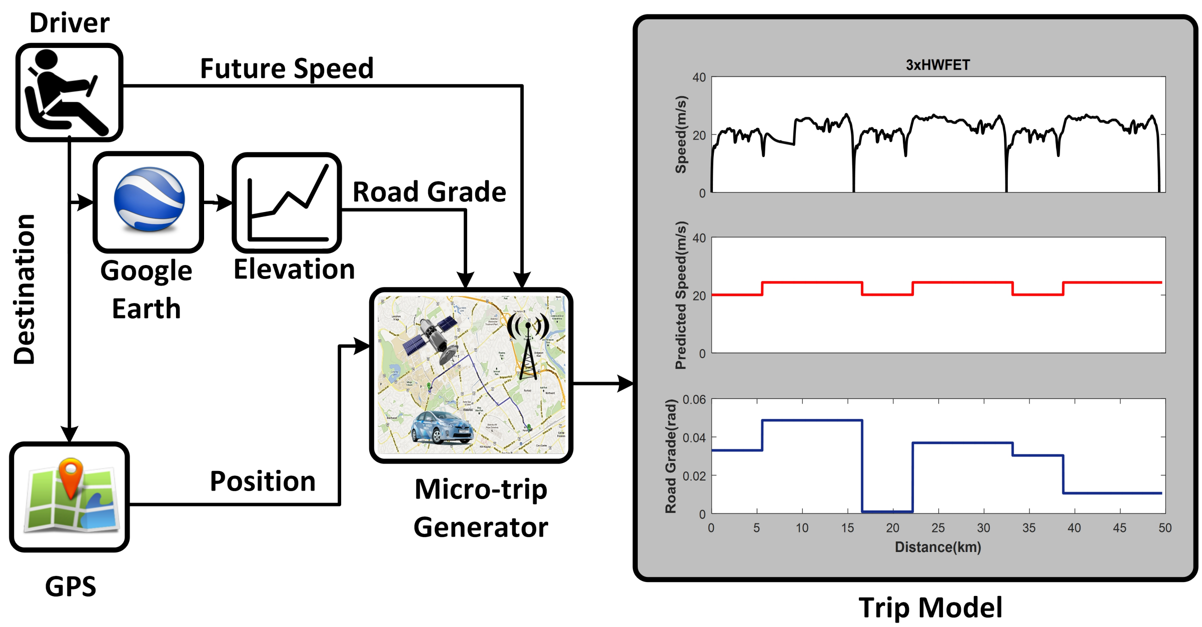

Figure 3.2: Micro-trip Generator module

train model, namely the online optimization power-balance model, to be used solely by the TP module. Besides, the use of RCO allows fast and relatively accurate solution, removing the potential bottlenecks that might arise during optimization [110].

3.3.1 Online Optimization Power-balance Model

The use of high-fidelity model, although accurate, is computationally demanding making it inappropriate for real-time/online applications. For this reason, the power-balance model is constructed, particularly for optimization purposes, where the main emphasis has put on fast computations and adequate accuracy.

To derive the power-balance model, using the vehicle's longitudinal dynamics, the demanded power can be derived from Eq. 3.1 as follows

$$P_d = (\frac{1}{2}\rho A C_d v^2 + mgf\cos\theta + mg\sin\theta + m\dot{v}).v, \tag{3.1}$$

where P_d denotes the power demand, θ is the road grade, A, m and v are the vehicle's frontal area, mass and speed, respectively, f is the rolling resistance coefficient, C_d indicates the drag coefficient and g represents the gravity acceleration.

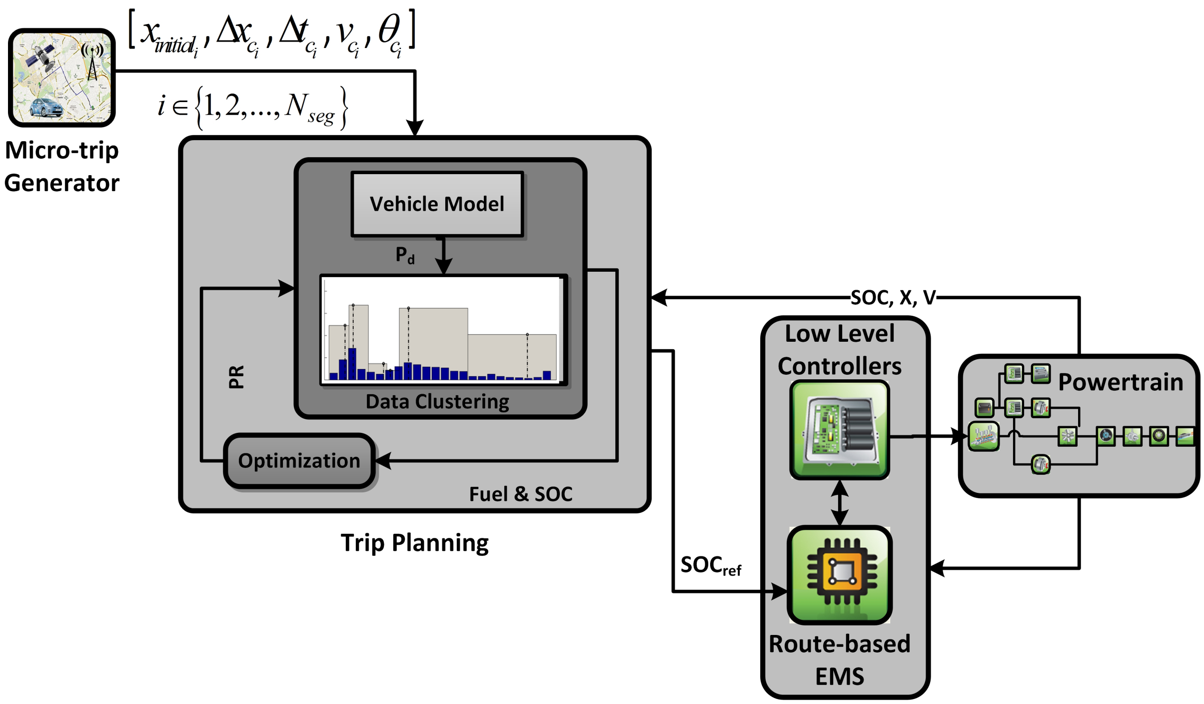

Figure 3.3: Schematic of the TP module

Power-split Model

The power split between the engine and the battery is defined as follows:

$$PR = \frac{\eta_m^\beta P_b}{P_d}, \tag{3.2}$$

$$P_e = \frac{1}{\eta_t}(P_d - \eta_m^\beta P_b) = \frac{P_d(1 - PR)}{\eta_t}, \tag{3.3}$$

where PR is defined as the power ratio, η_m^β is the motor-generator efficiency with $\beta = 1$ for battery discharging and $\beta = -1$ during battery charging, P_b and P_e are the power of the battery and engine, respectively and η_t is the efficiency of the transmission system.

Battery Model

The battery state of charge (SOC) is illustrated as the percentage of the current battery capacity over the maximum allowable capacity.

$$S\dot{O}C(P_b) = -\frac{I}{Q_{\max}} = -\frac{V_{oc} - \sqrt{V_{oc}^2 - 4P_bR_b}}{2R_bQ_{\max}}, \tag{3.4}$$

where I is the load current, $Q_{\max}$ is the maximum capacity, V_{oc} is the open circuit voltage and R_b is the battery internal resistance. It is worth mentioning that V_{oc} and R_b are assumed to be constant. In addition, $S\dot{O}C(P_b)$ can be linearly expressed as below [110]

$$S\dot{O}C(P_b) = -\eta_b \frac{P_b}{Q_{\max}}, \tag{3.5}$$

where η_b is the equivalent battery discharge power efficiency.

Fuel Consumption Model

According to [14], based on the efficiency map of the baseline PHEV engine, fuel consumption can be approximated by a linear function of the engine power which yields

$$\dot{m}_f(P_e) \approx m_0 + \alpha \times P_e, \tag{3.6}$$

where $\dot{m}_f$ is the fuel consumption of the segment, m_0 and α are design parameters.

Segment Modeling

Since the Micro-trip Generator produces the segmented micro trips which mainly consists of the cruise section, the equations of the cruise section can be finalized as follows

$$P_{d_c} = \frac{1}{2}\rho A C_d {v_c}^3 + (mg\mu\cos\theta + mg\sin\theta).v_c, \tag{3.7}$$

$$P_{b_c} = \frac{PR}{\eta_m} P_{d_c}, \tag{3.8}$$

$$P_{e_c} = \frac{(1 - PR)}{\eta_t} P_{d_c}. \tag{3.9}$$

The battery discharge can be simply modeled as

$$\Delta SOC = SOC_0 + \dot{SOC}.\Delta t. \tag{3.10}$$

Along the same lines, the fuel consumption can be modeled as

$$\Delta m_f = m_{f_0} + \dot{m}_f.\Delta t, \tag{3.11}$$

where SOC_0 and m_{f_0} are supposed to reflect the segments' specification such as the acceleration, declaration and cruise sections. However, since these three sections will be processed altogether to form a single new cruise profile, SOC_0 and m_{f_0} are considered to be a function of cruise speed, thus $SOC_0 = g_1(v_c)$ and $m_{f_0} = f_1(v_c)$. Moreover, using Eq. 3.5, it follows that $\dot{SOC} = g_2(P_b)$. In addition, according to Eq. 3.6, $\dot{m}_f$ is initially dependent on P_e, $\dot{m}_f = f_2(P_e)$. Nevertheless, these equations are very simple compared to the real-world energy consumption. Therefore, Eq. 3.10 and Eq. 3.11 should be empirically modified for better resemblance to the actual model and to compensate the effect of approximating the segment with an average cruise section. To further improve the accuracy of the model, a sensitivity analysis has been carried out and it was pointed out that using a linear function of cruise speed for Eq. 3.10 and a quadratic one for Eq. 3.11 will improve the accuracy of the energy consumption model. Therefore, the resultant model can be expressed as

$$\Delta SOC_c(P_{b_c}, v_c, \Delta t_c) = l_0 + l_1 v_c + (l_2 + l_3 P_{b_c} + l_4 v_c).\Delta t_c, \tag{3.12}$$

$$\Delta m_{f_c}(P_{e_c}, v_c, \Delta t_c) = k_0 + k_1 v_c + (k_2 + k_3 P_{e_c} + k_4 v_c + k_5 v_c^2).\Delta t_c, \tag{3.13}$$

where v_c is the cruise speed and Δt_c represents the cruise duration. The coefficients l_i and k_i are design variables that can be obtained by parameter estimation such as LS method [14]. A detailed discussion on this topic is given in Chapter 4.

3.3.2 TP Module Overall Configuration

As shown in the block diagram in Fig. 3.3, the TP module receives two sets of information, the updated segmented trip estimation from the micro-trip generator and the current states of the vehicle, which generally include speed, location and SOC. These data are then used to calculate the power demand of each trip segment. The TP module uses power demand as the basis for partitioning the trip segments into N_c clusters. This will facilitate the optimization process because every cluster is uniquely identified by a particular power ratio and the optimization algorithm will be required to seek the clusters instead of all the trip segments, potentially saving a lot of computations [110]. For the optimization, the RCO algorithm is employed which has the duty to minimize the total energy cost of both electrical grid energy and fuel consumption. In particular, it calculates the cost of each segment using Eq. 3.12 and Eq. 3.13, adds the obtained costs for all of the segments to formulate the objective function.

Finally, the acquired optimum power ratio along with the first predicted segment's specifications such as power demand and cruise speed are used to find the optimal SOC profile for the first estimated segment of the remaining part of the trip. This functions as the reference for updating the equivalency factor used in the Route-based EMS module, in order to optimally distribute the power between the engine and the motor-generators.

3.3.3 Optimization Problem

Optimization problem can be expressed as minimization of

$$\min J = \sum_{i=1}^{N_{seg}} f_i(PR_i), \tag{3.14}$$

$$f(PR) = \Delta m_{f_c}(PR) - \Delta SOC_c(PR), \tag{3.15}$$

subject to

$$P_{e_{\min}} \leq P_e \leq P_{e_{\max}}, \tag{3.16}$$

$$P_{b_{\min}} \leq P_b \leq P_{b_{\max}}, \tag{3.17}$$

$$P_{b_{\min}} \leq P_b \leq P_{b_{\max}}, \tag{3.18}$$

$$0 \leq PR \leq 1, \tag{3.19}$$

$$SOC_{\min} \leq SOC \leq SOC_{\max}, \tag{3.20}$$

where N_{seg} is the number of remaining segments to the end of the trip, the subscript i stands for each of the segments, $i \in \{1, 2, ..., N_{seg}\}$, $P_{e_{\min}}$ and $P_{e_{\max}}$ are the upper and lower bounds of the engine's power. Similarly, $P_{b_{\min}}$ and $P_{b_{\max}}$ show the allowable bounds on the battery's power. In addition, $SOC_{\min}$ and $SOC_{\max}$ indicate the acceptable range of the battery's SOC which can be expressed as follows

$$SOC_{initial}(t_{update}) = \begin{cases} SOC_{curent} & t_{update} > 0 \\ SOC_0 & t_{update} = 0 \end{cases}, \tag{3.21}$$

$$SOC_{final}(t_{update}) = SOC_{initial}(t_{update}) + \sum_{i=1}^{N_{seg}} \Delta SOC_{c_i}(PR_i), \tag{3.22}$$

$$SOC_{final}(t_{update}) = SOC_f, \tag{3.23}$$

where t_{update} indicates the update time i.e. the time that the TP module gets updated and the optimization problem should be solved, $SOC_{current}$ is the current SOC of the vehicle and SOC_0 shows the initial battery charge. The predicted final SOC ($SOC_{final}(t_{update})$) is calculated using Eq.3.22 which should meet the final desirable SOC (SOC_f) subject to the constraint Eq.3.23.

To solve the above optimization problem, the PSO algorithm is utilized which is described in the next sub-section.

3.3.4 Partcile Swarm Optimization

Proposed by Eberhart and Kennedy [111], Particle Swarm Optimization (PSO) is one of the fundamental variants of swarm intelligent based techniques which simulates the collective behavior of self-organizing species (in particular fish schooling). As a heuristic search method, PSO's searching strategy is based on the interaction of particles in a local region and also with the leading particle. This provides the algorithm with a balance between intensification and diversification of search which often leads the particles escaping from local traps and finding the global (or a qualified) optimum solution. This algorithm has been used in various optimization problems in engineering; see [112, 113, 114] and references therein. Also, in the context of EMS module design for PHEVs, it is mentioned that PSO leads to faster optimizations when compared to other derivative-free algorithms [115].

As a stochastic iterative solution, PSO follows a number of steps and certain updating rules to optimize the objective function. At iteration t, the position of the i^{th} particle can be defined as $\bar{\mathbf{x}}_i^t = \left[x_i^t(1), x_i^t(2), ..., x_i^t(D)\right]^T$ where D is the dimension of the optimization problem. If the population of swarms hosts m particles, the population matrix can be denoted as $\mathbf{X} = \left[\bar{\mathbf{x}}_1^t, ..., \bar{\mathbf{x}}_m^t\right]^T$. There are two important elements in the algorithmic functioning of PSO which guide the search, i.e. the local best solution *lbest* and the global best *gbest* solution. Let *lbest* and *gbest* vectors described by $\bar{\mathbf{l}}_i = \left[l_i(1), l_i(2), ..., l_i(D)\right]^T$ and $\bar{\mathbf{g}} = \left[g(1), g(2), ..., g(D)\right]^T$, respectively. At iteration t, the velocity of the i^{th} particle is defined as $\bar{\mathbf{v}}_i^t = \left[v_i^t(1), v_i^t(2), ..., v_i^t(D)\right]^T$. The updating rule of PSO can be defined as

$$\bar{\mathbf{v}}_i^t = \omega\, \bar{\mathbf{v}}_i^{t-1} + \mathbf{c}_1 r_1 \left(\bar{\mathbf{l}}_i - \bar{\mathbf{x}}_i^{t-1}\right) + \mathbf{c}_2 r_2 \left(\bar{\mathbf{g}} - \bar{\mathbf{x}}_i^{t-1}\right), \tag{3.24}$$

where ω is the inertia weight, $\mathbf{c}_1$ and $\mathbf{c}_2$ are two positive constants and r_1 and r_2 are two random parameters within $[0, 1]$. The above updating rule calculates the particle's new velocity based on the local best, global best, and distance. After updating the velocity of each particle, the following equation is used

$$\bar{\mathbf{x}}_i^t = \bar{\mathbf{x}}_i^{t-1} + \bar{\mathbf{v}}_i^t. \tag{3.25}$$

To further assist the search of PSO, the following updating rule is considered for the inertia weight

$$\omega = \omega_{\max} - \frac{t}{T}\left(\omega_{\max} - \omega_{\min}\right), \tag{3.26}$$

where $\omega_{\min}$, $\omega_{\max}$, and T are the design paramters.

3.4 Route-based EMS

3.4.1 Control-oriented Model

The control-oriented model is identical to the power-balance model in terms of power-split model (Eq. 3.2 , Eq. 3.3), battery model (Eq. 3.5), and fuel consumption model (Eq. 3.6), but in terms of power demand, it uses the instantaneous power demand based on the driver's command instead of using the predicted speed.

3.4.2 Route-based ECMS

This module divides the power demand between the engine and the motor-generators by using the momentary demanded power. For this purpose, the Route-based Equivalent Consumption Minimization Strategy (R-ECMS) [116] is employed within this module. This method has fundamentally exploited the ideas from the Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) [117]. A-ECMS utilizes a linear reference SOC profile in terms of the trip length to adaptively adjust the equivalency factor between the energy sources.

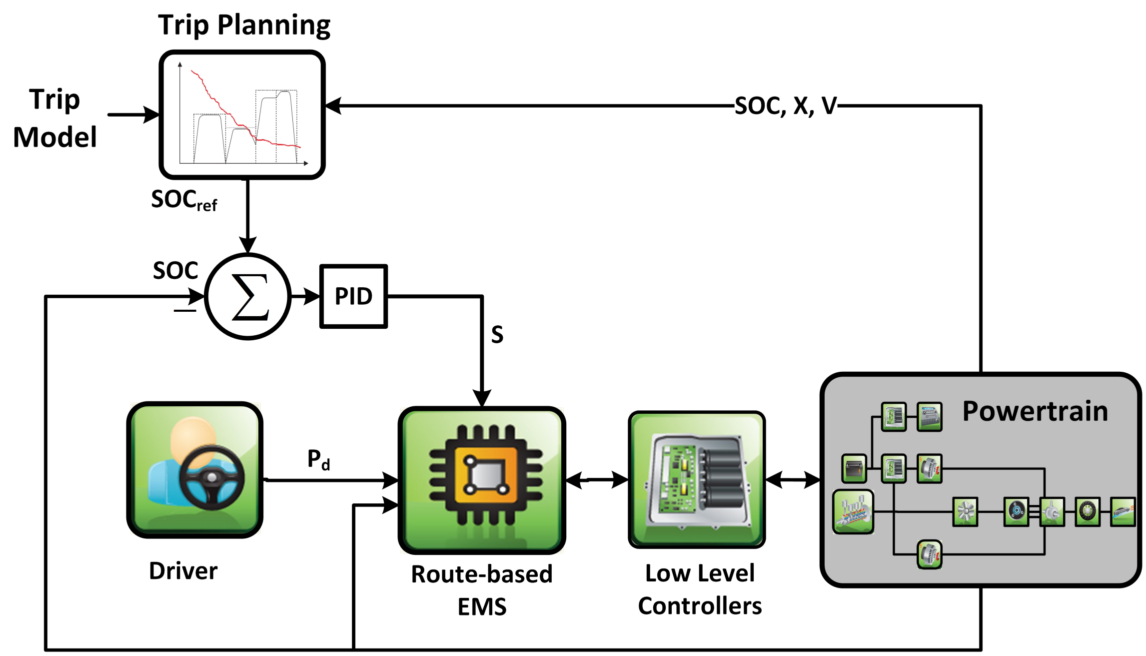

Figure 3.4: Schematic of the Route-based EMS

Fig. 3.4 presents the Route-based EMS schematic. R-ECMS obtains the optimum predicted SOC and uses it as a reference SOC (SOC_{ref}) along with a PID controller to update the equivalency factor during the trip. The obtained optimum SOC profile enables the Route-based EMS to optimally distribute the power between the engine and motor-generators in a real-time fashion. The cost function should include both fuel consumption and the electrical energy which can be defined as:

$$Cost = C_f \dot{m}_f - C_e \eta_{ch} Q_{max} \dot{SOC}, \tag{3.27}$$

where $\dot{m}_f$ is the fuel consumption, η_{ch} indicates the charger efficiency, Q_{max} represents the maximum battery capacity, C_f, and C_e are the unit price of gas and grid electrical energy, respectively. By considering the PR as an input, SOC as a system state, and the above cost function, the optimal control problem can be formulated as follows

$$J = \int_0^{t_f} \left(C_f \dot{m}_f - C_e \eta_{ch} Q_{max} S\dot{O}C \right) dt, \tag{3.28}$$

Subject to:

$$SOC\,(0) = SOC_0, \tag{3.29}$$

$$SOC\,(t_f) = SOC_f, \tag{3.30}$$

$$SOC_{min} \leq SOC \leq SOC_{max}, \tag{3.31}$$

$$P_{b,min} \leq P_b \leq P_{b,max}, \tag{3.32}$$

$$P_{e,min} \leq P_e \leq P_{e,max}, \tag{3.33}$$

To solve the optimal control problem, first, the real-time algorithm based on equivalent consumption minimization strategy (ECMS) can be developed as

$$J = \int_0^{t_f} (C_f \dot{m}_f - S C_e \eta_{ch} \eta_b P_b) dt, \tag{3.34}$$

where S is the equivalency factor defined to adjust the supply and demand of the battery as a matter of capacity limitation. This equivalency factor is highly dependent on the future drive cycle. To deal with this issue, an adaptive ECMS (A-ECMS) is employed which uses the optimal SOC profile provided by the previous module as the reference SOC along with a PID controller to obtain the equivalency factor S.

Table 3.1: Toyota Prius PHEV characteristic

Parameter	Symbol	Value	Unit
Vehicle mass	m	1525	kg
Frontal area	A	2.25	m^2
Drag coefficient	C_d	0.26	-
Motor power	P_m	50	kW
Generator power	P_g	30	kW
Engine power	P_e	73	kW
Battery nominal capacity	Q	21	Ah
Battery cell nominal voltage	V	3.7	V
Number of battery cells	N_b	56	-
Wheel radius	r	0.3	m

3.5 Powertrain High-fidelity Model

3.5.1 2013 Toyota Prius PHEV Powertrain Structure

This study has been carried out for a 2013 Toyota Prius PHEV. Table 3.1 presents the characteristics of this vehicle [14]. As illustrated in Fig. 3.5, an IC engine and two electric machines that can be used as either a motor or a generator are the main components of the vehicle's powertrain. Two planetary gear sets linking the two electrical motors, called MG-1 and MG-2 to the wheels create a power-split transmission system.

The first planetary gear's sun gear and courier are coupled to the MG-1 and the engine, whereas, in the second set, the sun gear and courier are coupled to the MG-2 and the chassis. Also, the wheels are coupled to the ring gears of both sets. By means of this power-split structure, the operation of the engine can be adjusted to achieve maximum fuel efficiency. In fact, the main objective of the EMS is the minimization of fuel consumption and can be obtained by managing the functionality of MG-1 and MG-2. The power distribution occurs based on some rules, e.g. it is better for the fuel economy that in the case of low speed and driving from standstill the engine be turned off; therefore, the thrusting should take place through use of MGs. Also, the engine's power can be distributed in two power streams, one is used for the vehicle propulsion, and the other one is fed into the MG-1 which acts as a generator to produce the electricity. The electricity, will then be transmitted to MG-2 to generate mechanical power at the final drive.

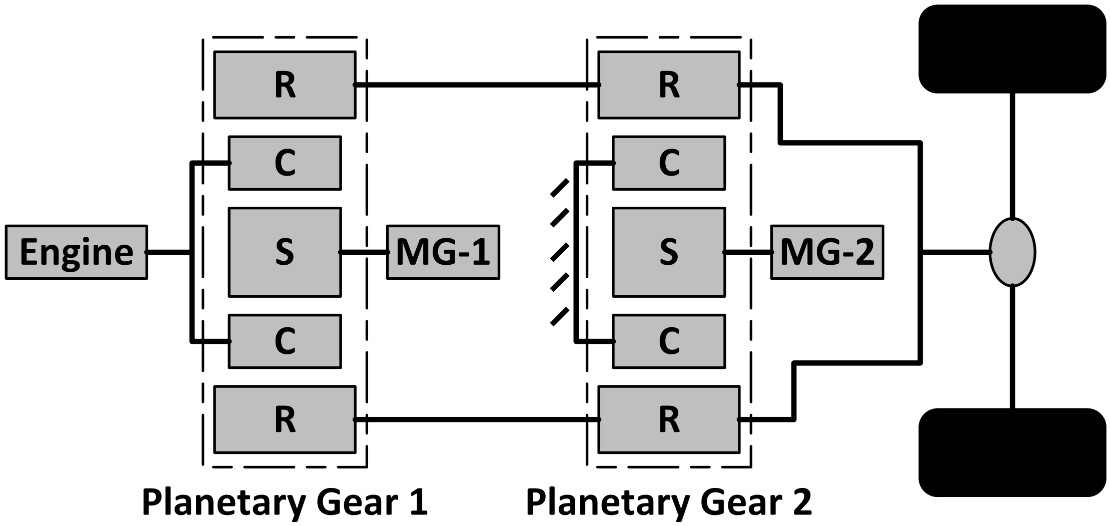

Figure 3.5: Powertrain layout of Prius 2013

3.5.2 Autonomie Model

The high-fidelity model used throughout this work has been constructed by using the Autonomie software produced by Argonne National Lab. This model has been validated in [60] and mainly consists of the model of the engine, MG-1, MG-2 and the battery pack.

Fig. 3.6 shows the Simulink model of the PHEV in Autonomie. It includes four main blocks as the environment, driver, vehicle powertrain controller (VPC), and vehicle powertrain architecture (VPA). These blocks communicate through buses with the main one leaving VPA once it collects all the data from VPA, then it transfers the signals to the other three blocks [118].

It should be pointed out that the Autonomie model originally contains a rule-based EMS, which is used as the benchmark in this research. On the other hand, our desired system is created by replacing the rule-based EMS with the TP-assisted EMS within the VPC block for controller evaluation purposes.

3.6 MIL Testing

Three main test scenarios are considered for evaluation of the developed TP-assisted EMS. In first set of simulations, the performance of the controller over a hilly road is evaluated.

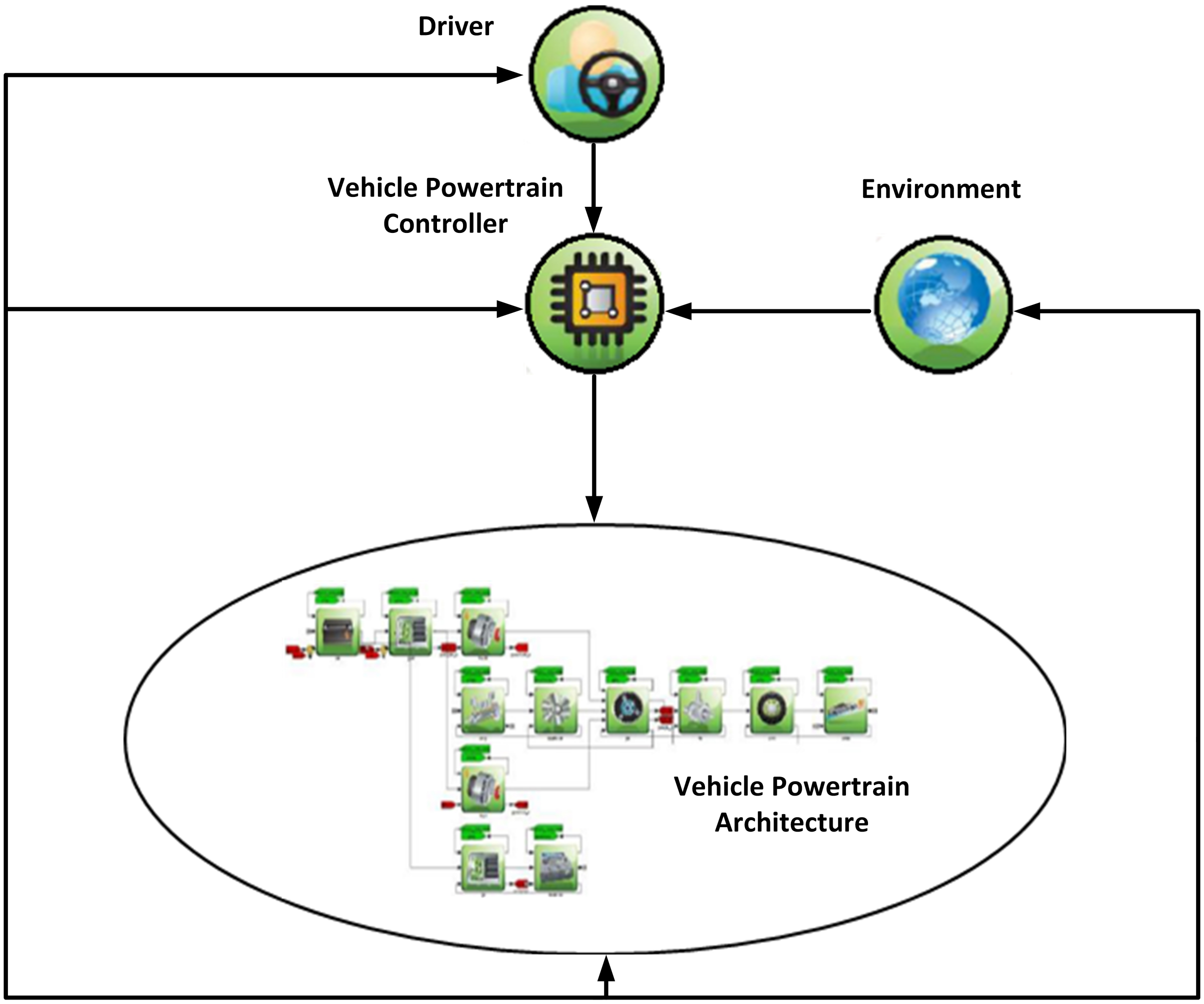

Figure 3.6: PHEV Autonomie blocks

The second subsection illustrates the controller's performance under standard drive cycles, and the last set of simulations have been carried out over real-world drive cycles. It should be pointed out that the trip length of all of the drive cycles considered here is more than the full electric range of the baseline vehicle to ensure that the battery is fully discharged at the end of the trip, and therefore, the engine gets the chance to drive the vehicle.

Table 3.2: Comparison between different EMS strategies

Standard Drive Cycles	TP-assisted EMS	Linear SOC_{ref} A-ECMS	Rule-based Autonomie
3xUDDS	108.27	104.7	97.7
3xSFTP	60.04	58.4	52.1
2xWLTP	79.12	78	72.7
EPA_UHU	102.04	98.3	95.1
3xHWFET	93.7	92.8	79.3

3.6.1 Road Grade Testing

This section presents the simulation results of a drive cycle over a section of Calgary to Vancouver route, in Canada. The road elevation has imported from Google Earth, and a constant speed of 25 m/s is considered to be followed. Fig. 3.7 illustrates the energy consumption over the mentioned trip. It is shown the TP-assisted EMS can help maintain the battery charge to the end of the trip, and therefore, results in a lower fuel consumption.

3.6.2 Standard Drive Cycles

It is aimed to evaluate the developed TP-asssietd EMS performance with respect to its counterparts such as rule-based EMS and A-ECMS. Figs. 3.8-3.10 show the simulation results for three standard drive cycles. The first drive cycle, 3xHWFET, consists of three standard HWFET drive cycles. Similarly, the second drive cycle, 3xUDDS, consists of three standard Urban Dynamometer Driving Schedule (UDDS) drive cycles. The third drive cycle, EPA-UHU, consists of two standard UDDS drive cycles at the start and end, and a HWFET drive cycle at the middle of the trip. These figures illustrate that the TP-assisted EMS is superior in terms of fuel consumption improvement. Also, the results of the EMS methods for different standard drive cycles are shown in Table 3.2 showing that in all scenarios, the best result are obtained by TP-assisted EMS.

3.6.3 Real-world Drive Cycles

In order to further examine the performance of the devised TP-assisted EMS, an extensive simulation have been carried out using real-world data provided by Chargecar [119] which include 60 different real-world drive cycles belonging to a verity of routes from all different locations in North America. Both TP-assisted EMS and rule-based EMS have been tested for all of these 60 drive cycles. Figs. 3.11-3.12 show the probability distribution function

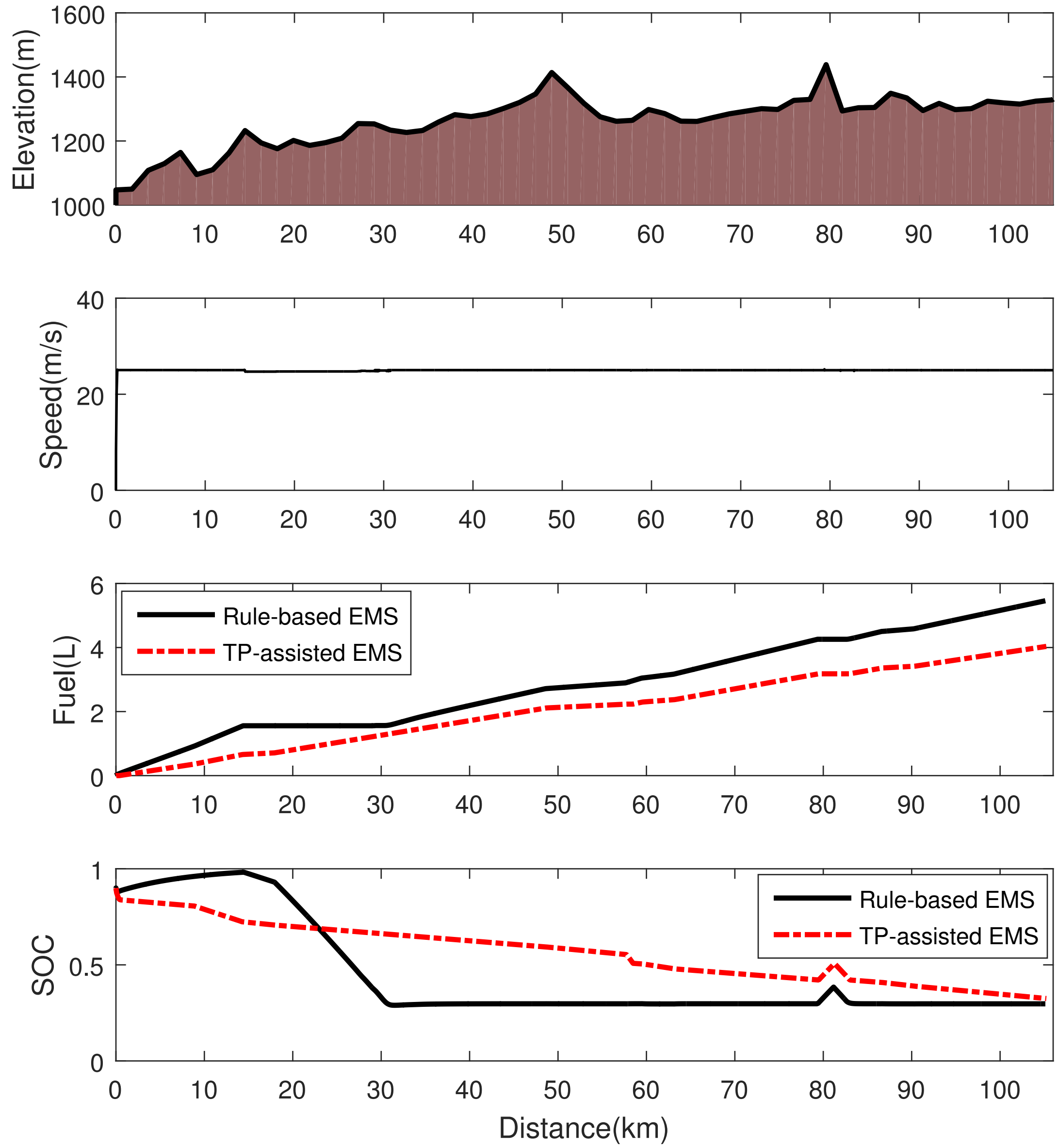

Figure 3.7: Simulation results for Prius equipped with TP-assisted EMS traveling a section of Calgary-Vancouver road

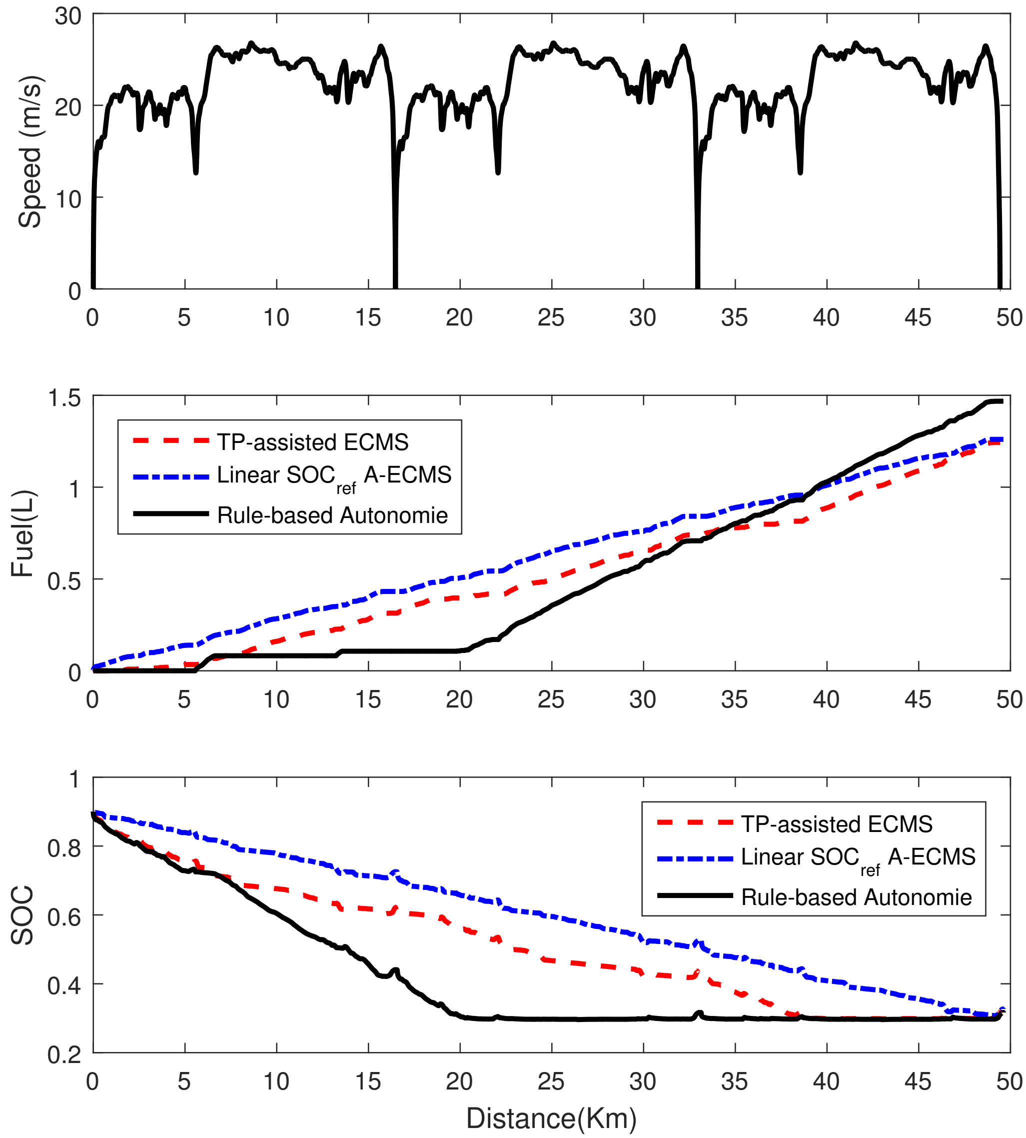

Figure 3.8: Simulation results for Prius equipped with TP-assisted EMS traveling 3xH-WFET drive cycle

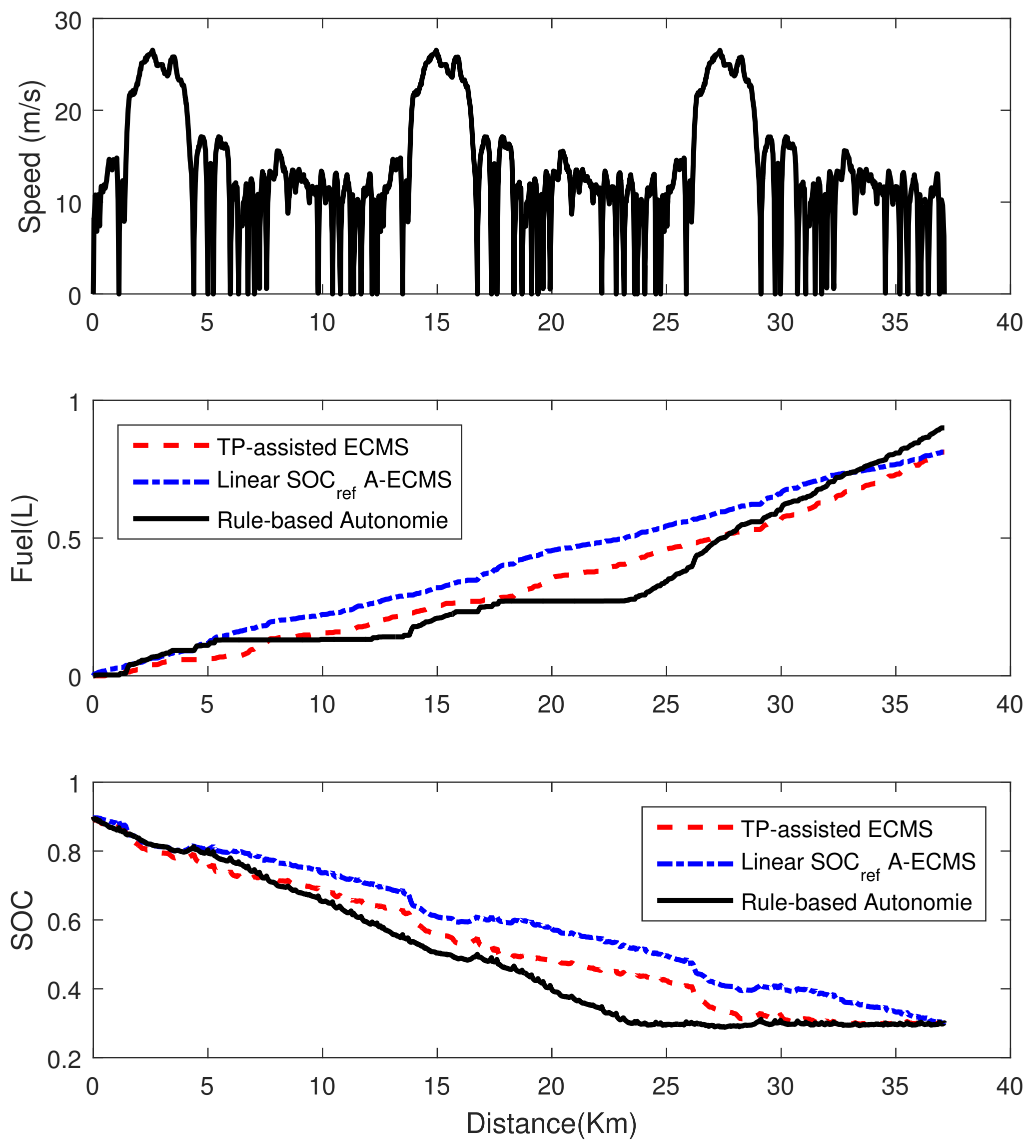

Figure 3.9: Simulation results for Prius equipped with TP-assisted EMS traveling 3xUDDS drive cycle

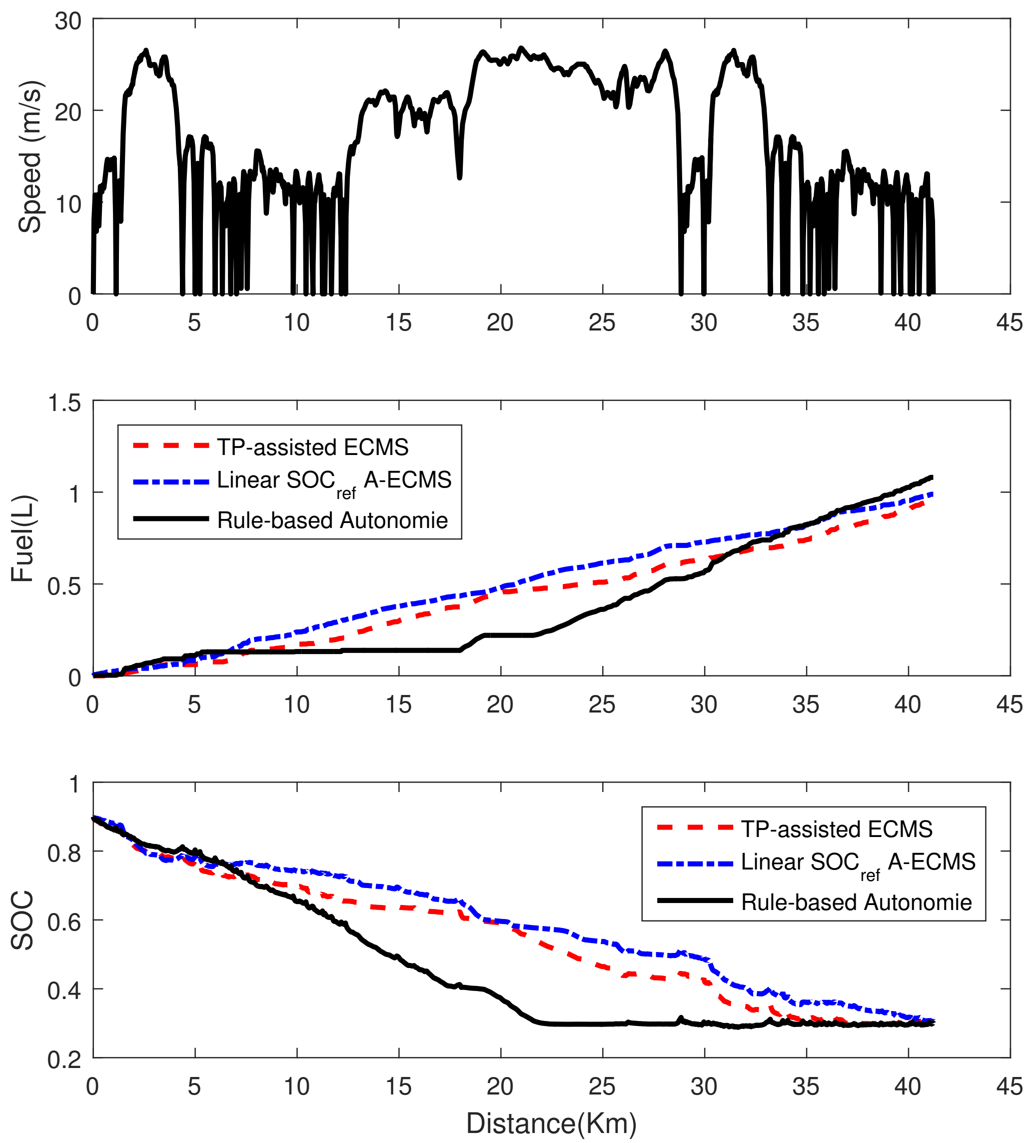

Figure 3.10: Simulation results for Prius equipped with TP-assisted EMS traveling EPA-UHU drive cycle

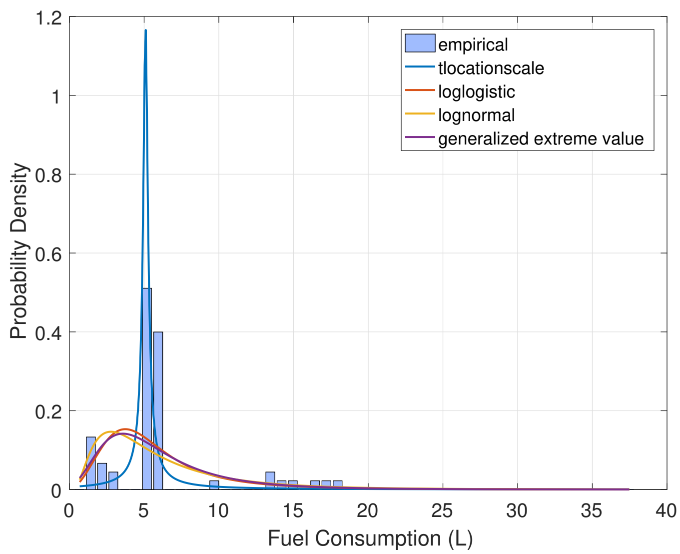

Figure 3.11: PDF of the fuel consumption of 60 real-world drive cycle using Rule-based EMS

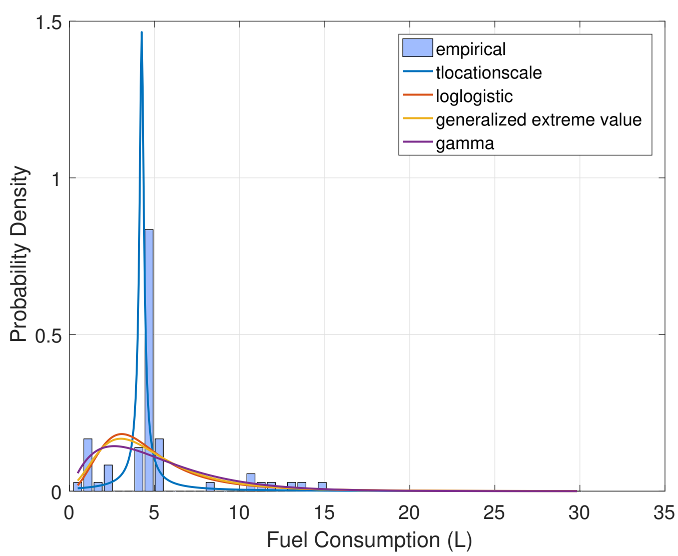

Figure 3.12: PDF of the fuel consumption of 60 real-world drive cycles using TP-assisted EMS

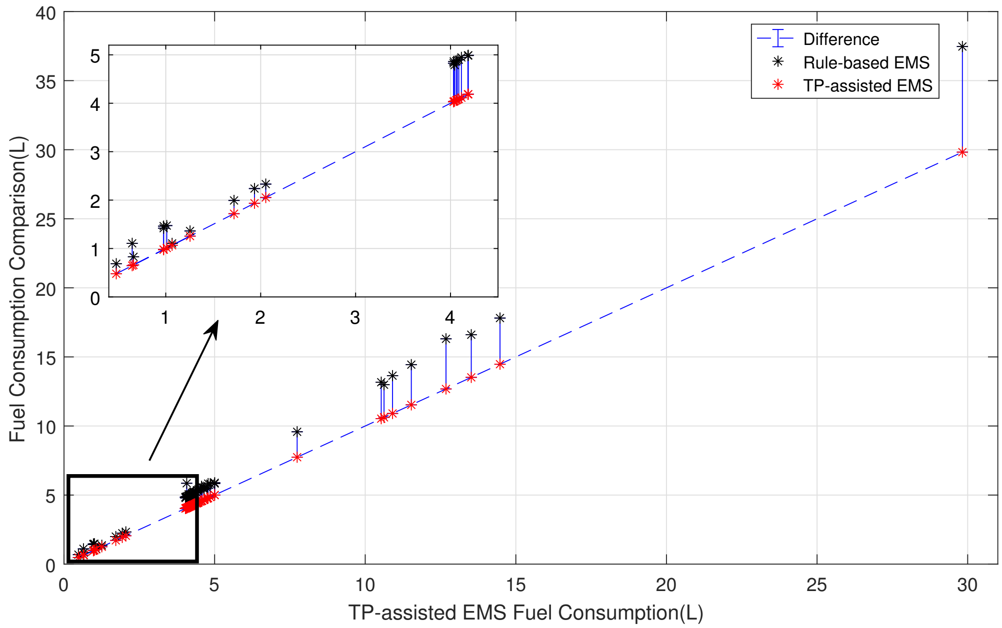

Figure 3.13: Comparison between TP-assisted EMS and Rule-based EMS

(PDF) of the fuel consumption for both methods where the MATLAB's $allfitdist$ function is used to fit all valid parametric probability distributions to data. These figures show that TP-assisted EMS and rule-based EMS function similarly.

These results are also numerically presented in Table 3.3 where μ, σ, and cv indicate the average, standard deviation and the coefficient of variation of the fuel consumption of the 60 drive cycles, respectively. The coefficient of variation is defined as

$$cv = \frac{\sigma}{\mu}. \tag{3.35}$$

Table 3.3: Fuel consumption(L) for 60 real-world drive cycles

EMS	μ	σ	cv
TP-assisted EMS	5.1359	4.4129	0.8592
Rule-based Autonomie	6.2736	5.5451	0.8839

Furthermore, the difference between the fuel consumption of these two EMSs is depicted in Fig. 3.13. It is important to note that the TP-assisted EMS outperforms rule-based

EMS when fuel consumption is higher which refers to longer drive cycles. This highlights the effect of maintaining the battery's charge over the trip while in the rule-based the battery is depleted all in once almost at the beginning of the trip.

3.7 HIL Testing

In the automotive industry, the embedded systems that communicate with various sensors and actuators to control different parts of the vehicles are referred as Electronic Control Units (ECUs). They are extensively utilized in various control applications including control of vehicle components such as transmission, engine, brake and suspension, cruise control and driver assistance systems. The number of applied ECUs in a modernized vehicle can be up to 80 [120]. This significant number of applied ECUs in vehicles requires reliable test benches to be used for both development and validation. As accurate, practical and cost-effective test benches for assisting the real-time control evaluation, HIL simulations can be considered for rapid prototyping of ECUs especially at their early development stages and before the real-time controller employment.

This work uses a HIL simulation to evaluate the real-time implementation capabilities of the TP-assisted EMS controller. A real-time simulator and two ECUs are the three main parts of the applied HIL set-up which are interconnected via a Controller Area Network (CAN). The high-fidelity model is implemented by the simulator, in this case, a DS1006 processor board and the TP module as well as the Route-based EMS controller are implemented by two MicroAutoBox II ECUs. Defining the time step to be the response time of the system or the update-rate of the input signals, the desired time step for the Route-based EMS controller is 1 ms. As for the TP module, the update rate is limited to the update rate of the traffic data, which is considered to be 100 s in our problem; therefore the time step is set 100 s. The HIL results for 3xHWFET drive cycle with six segments in total and the above time steps are demonstrated in Fig. 3.14 which confirms the consistency of the HIL results with those of MIL. One important factor in evaluation of the real-time feasibility is the turnaround time of the controller which must be smaller than the time step. The turnaround time is known as the time interval to perform the control computations and generate the ECU outputs. As shown in Fig. 3.14, this value does not exceeded 5 ms for the whole trip. This, compared to the update rate of the TP module (once per 100 seconds), confirms the real-time feasibility of the TP-assisted EMS. The HIL results also reveal that the turnaround time remains constant for each individual segment; however, it decreases over the time from one segment to the other. The reason is that the information of all the upcoming segments are required for optimizations. As the trip

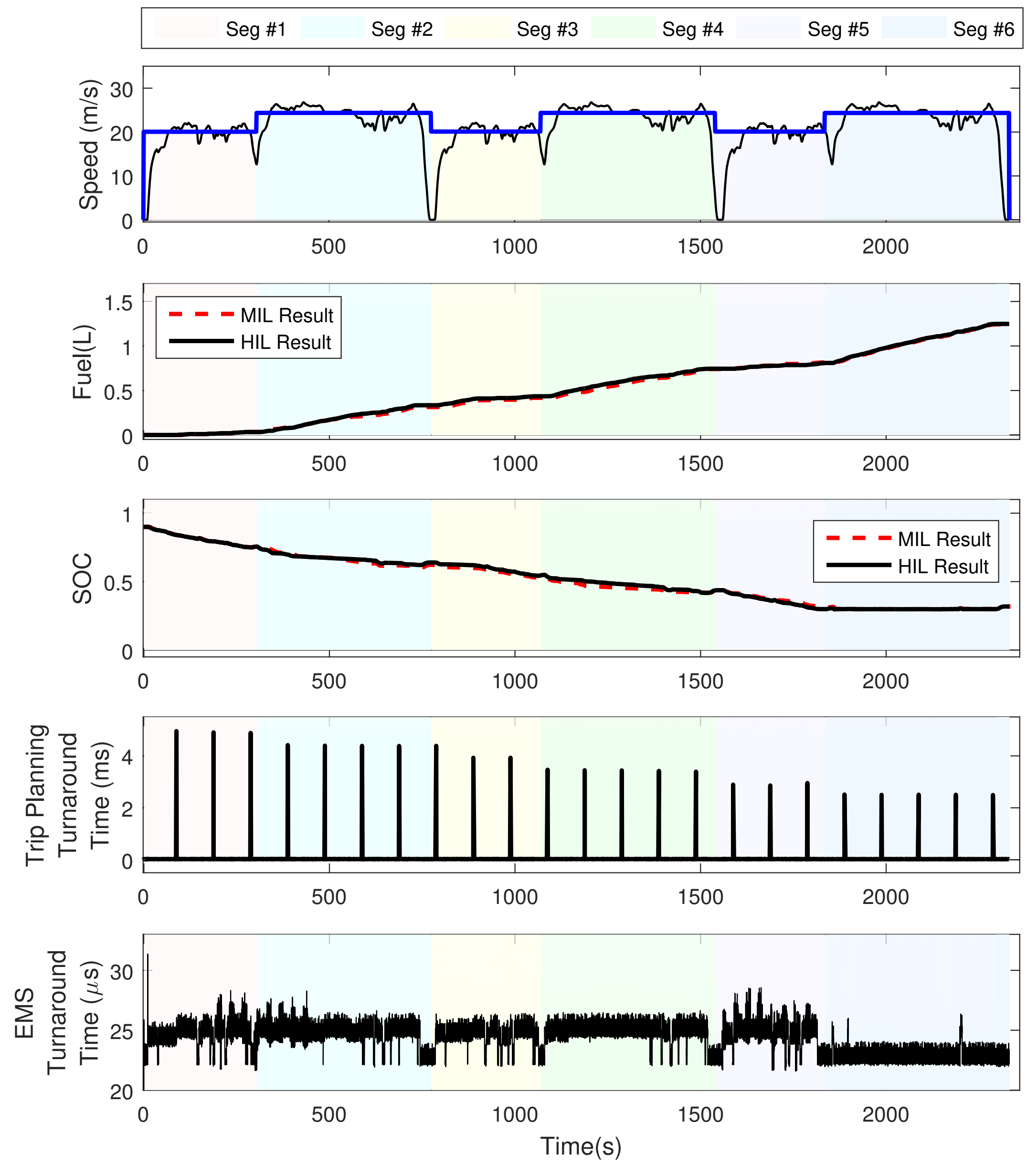

Figure 3.14: HIL results for Prius equipped with TP-assisted EMS traveling 3xHWFET drive cycle. Different background colors show disparate segments.

progresses, there will be a fewer number of the upcoming segments which results in a lower computational load for the optimization. Furthermore, it is noted that the turnaround time for the Route-based EMS is less than 35 μs which is much less than the defined time step (1 ms).

The results meet the requirements of the real-time implementation, and therefore, verify the feasibility of the proposed TP-assisted EMS controller to be used in the real-world problems.

3.8 Summary

This chapter presented the architecture of the TP-assisted EMS module suitable for online implementation in a PHEV. It is shown that the use of power-balance model and PSO for optimization purposes will improve the computational efficiency of the module so that it can be implemented in an online setup. This has been verified through HIL testing. The performance of the module in improving the fuel efficiency has been also tested in various scenarios including standard drive cycles, hilly road and 60 real-world scenarios, which verifies the effectiveness of the design. Throughout these tests, it has been revealed that the TP-assisted EMS provides better fuel efficiency compared to A-ECMS and rule-based EMS, two conventional energy management strategies in the present PHEVs.

Chapter 4

Soft-computing based Trip Planning

This chapter incorporates soft-computing techniques for trip planning of PHEVs, studying the impact of these methods on modeling of energy consumption and how they will reflect in SOC profile predication. The chapter starts with a description of data generation to be used for both training and validation purposes. Building upon this data set, a gray-box as well as a black-box model have been developed. For the gray-box case, the modeling task is translated into an optimization problem and the Particle Swarm Optimization (PSO) algorithm is employed to find the optimum solution. In case of black-box modeling, the advantages of fuzzy inference systems and neural networks have been harnessed in an adaptive neuro-fuzzy inference system (ANFIS) to develop an accurate and computationally inexpensive model. Several numerical simulations have been carried out and statistical analyses have been presented to compare the methods and verify their effectiveness.

4.1 Data Set Generation

The first step for modeling is to generate an appropriate data set, to be used in both model identification and validation phases, such that along with the soft-computing techniques lead to a realistic description of the energy consumption. The key for proper data generation is to use the high-fidelity model. With this in mind, two data sets of the input segmented trip information are generated, with the intention to include most, if not all, of the possible scenarios that can be experienced in a micro trip. Therefore, different segment's characteristics such as various initial/final speeds, cruise speed, segment's length/time, etc. are taken into account. These data sets are then fed into the Autonomie high-fidelity model and the output is acquired in two separate sets, one for testing and the other for training purposes. This forms two inclusive collections of data which both contain randomized yet realistic inputs paired with their expected outputs.

4.2 Gray-box Modeling of Energy Consumption

The gray-box modeling uses a partially known mathematical structure of the system and implements optimization techniques to estimate the system parameters in order to enhance the formerly known mathematical model. Since the underlying equations of energy consumption are already derived in Chapter 3, the gray-box modeling is a feasible candidate to estimate the system parameters and consequently model the energy consumption accurately.

As discussed earlier, Eq. 3.12 on page 28 and Eq. 3.13 on page 28 have been empirically developed to find out the amount of battery discharge, ΔSOC_c, and the fuel consumption, Δm_{f_c}, in each of the segments during online optimization. These equations include various coefficients which are not accurately known. The gray-box modeling translates the problem into an optimization formulation where it is desired to find the most optimum values for the decision vector $\bar{\Phi} = \begin{bmatrix} l_0 & l_1 & l_2 & l_3 & l_4 & k_0 & k_1 & k_2 & k_3 & k_4 & k_5 \end{bmatrix}^T$ such that the modeling error is minimized.

Having established the decision vector, the empirical model can be rewritten in a linear parametric form as

$$\rho = f(\theta, \bar{\Phi}) \tag{4.1}$$

where ρ and θ refer to the output and input in each pair of the data set introduced in Section 4.1. The cost function utilized in the optimization is RMSE defined as

$$RMSE = \sqrt{\sum_{j=1}^{N} \left(\rho(j) - \theta(j)\hat{\Phi}\right)^2}, \tag{4.2}$$

where N is the data set size and $\hat{\Phi}$ is an estimation of $\bar{\Phi}$. The PSO algorithm explained in Chapter 3 is used to find the global minimum of Eq. 4.2.

4.3 Black-box Modeling of Energy Consumption

Black-box modeling is based on the assumption that no prior knowledge of the system model is available. A set of input-output data is then used to tune a mathematical model that mimics the system behavior. There are various tools available to implement the mathematical model. However, since the the goal of this chapter is to investigate the application of soft-computing techniques, an ANFIS structure has been employed.

ANFIS is a variant of fuzzy inference systems that takes advantage of the learning strategy used in ANN to optimally tune the identifiable parameters. Performance of ANFIS has been verified through extensive theoretical and practical studies published in the literature; see [121, 122] and references therein. Such high estimation accuracy is because ANFIS integrates the approximation capability and robustness of fuzzy inference systems with the adaptability of neural networks that is mainly due to the learning algorithms.

Implementation of ANFIS requires a systematic stepwise procedure described below:

Step 1: Fuzzification of the input features which can be done via transferring the crisp input vectors to K_i fuzzy linguistic expressions $\{A_1(j), A_2(j), ..., A_{Ki}(j)\}$, where $j = 1, ..., r$. Based on a prior sensitivity analysis, Gaussian functions are deemed the best membership functions to be used for modeling in this study.

Step 2: Once the structure of antecedent rules has been fixed, the linguistic terms are fed to the neurons of hidden layers (each neuron represents a single rule of the rule base) to form a set of rules. ANFIS uses Takagi Seugeno Kang (TSK) technique to build up the rule base [123] as

$$R = \prod_{j=1}^{r} k_j. \tag{4.3}$$

The i^{th} rule $(i = 1, ..., m)$ in the rule base can be represented as

$$R^{(i)}: \; IF\, x_1\, is\, A_{i_1}^{(r)}\, AND \ldots AND\, x_r\, is\, A_{i_r}^{(r)}\; THEN\, y^{(i)} = g^{(i)}. \tag{4.4}$$

It is worth mentioning that the consequent part of fuzzy rules is set to be a constant ω.

Step 3: The firing rate of each rule is defined as

$$\mu_i(x) = \prod_{j=1}^{r} \mu_{i_j}^{(i)}(x_j). \tag{4.5}$$

Step 4: The overall crisp output can be obtained using weighting average (WA) defuzzification technique given by

$$y_o = \sum_{i=1}^{m} \frac{\mu_i(x)}{\sum\limits_{i=1}^{m} \mu_i(x)} . g^{(i)}. \tag{4.6}$$

To train ANFIS, the classic back propagation (BP) algorithm has been implemented which requires the following steps. Assume that N samples are available to train the model. Then, the prediction error can be calculated as

$$e = y_d - y_{pred} = \sum_{j=1}^{N} g_j.(y_{d,j} - y_{pred,j}). \tag{4.7}$$

Based on the calculated error, the adjustable parameters of ANFIS (including consequent and antecedent parts of the rule base) can be optimized using steepest descend updating rule [124]

$$C_j(t+1,i) = \gamma C_j(t,i) - \eta e(j) g_j (y_{d,j} - y_{pred,j}) \left(\frac{x_i - C_j(t,i)}{\sigma_j^2(t)} \right), \tag{4.8}$$

$$\sigma_j(t+1) = \gamma \sigma_j(t) - \ \eta e(j) g_j (y_{d,j} - y_{pred,j}) \left(\frac{\sum_{i=1}^{2} (x_i - C_j(t,i))^2}{\sigma_j^3(t)} \right), \tag{4.9}$$

$$w_j(t+1) = \gamma w_j(t) - \eta e(j) g_j, \tag{4.10}$$

where η stands for the learning rate, γ represents the momentum, $y_{d,j}$ denotes the j^{th} desired output, $y_{pred,j}$ indicates the prediction of ANFIS for j^{th} sample, i is the i^{th} feature of the input vector, and t is the t^{th} step of BP learning. As a rule of thumb, the momentum is added to the updating rule to prevent the premature convergence of training process.

4.4 Simulation Results

This section presents the numerical studies that have been performed for gray-box and black-box modeling of energy consumption following by a statistical analysis and detailed discussion of the results.

Throughout the simulations the design parameters were set based on the reports given in the literature as well as the assessments made in the sensitivity analysis. For the PSO algorithm, the iteration number is set to 50. The value of $\omega_{\max}$ is set to 1.72. The parameters c_1 and c_2 are both equal to 2. Also, the number of particles used in the optimization is 10. Based on the sensitivity analysis results, 7 membership functions (MFs) of Gaussian type are considered in implementations of the ANFIS model and BP is used

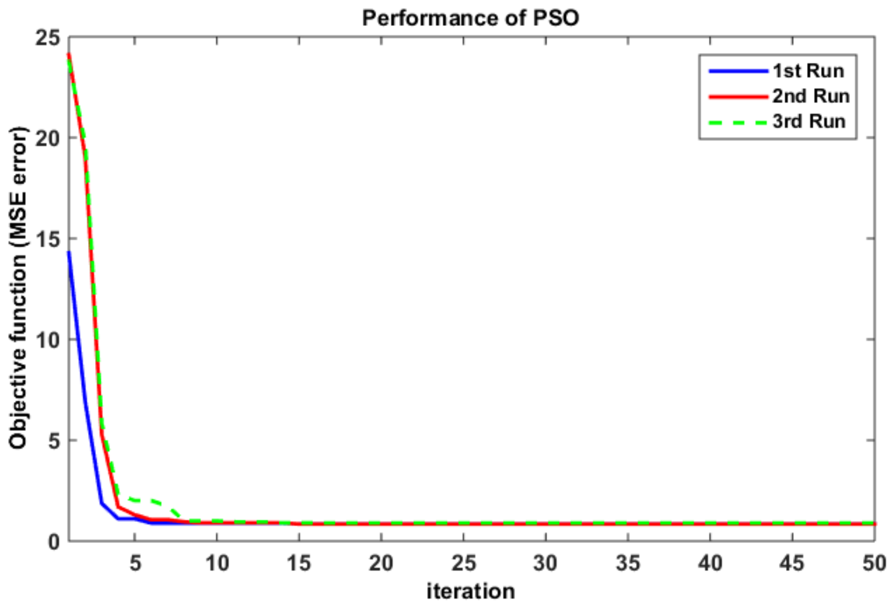

Figure 4.1: Evolution of global best solution of PSO over the optimization process

for training. Each simulation scenario has been carried out in 30 independent runs, and the statistical results are reported by means of mean value and standard deviation (std.) metrics. This can be mathematically expressed as

$$Mean\ ObjVal = \frac{1}{P_S}\sum_{i=1}^{P_S} ObjVal(X_i), \tag{4.11}$$

where P_S shows the population size. Also, std. value can be obtained by calculating the square root of variance.

The gray-box model has been obtained by using PSO optimization and its accuracy is evaluated by means of mean square error (MSE) obtained during both training and testing steps. To evaluate the robustness of PSO, three different initial points are considered to start the optimization, and for each initialization the optimization is repeated 10 times in order to have 30 independent runs. The mean performance of each test was calculated and presented in Fig. 4.1. As observed, PSO requires less than 10 iterations to solve the optimization problem. Furthermore, the results indicate repeatability despite variation of the initial conditions. More importantly, all the trajectories converge to a unique solution without any deviation, implying the robustness of the results against the randomness of the test data.

For the black-box model identification, the learning data set has been used to train ANFIS and its modeling accuracy has then compared against the PSO results in Tables. 4.1 and 4.2. These results show that ANFIS has up to one order of magnitude smaller MSE compared to PSO and meanwhile exhibits lower std., too. In addition, the training time for ANFIS was measured less than 3 seconds which is two order of magnitude faster than the computation time required for PSO. This is particularly important in online trip planning module where SOC trajectories need to be quickly generated. Therefore, better accuracy and computational efficiency of ANFIS makes it a superior choice for modeling of energy consumption over PSO.

Table 4.1: Comparison of different estimation algorithms for ΔSOC_c

Method	MSE Train	MSE Test	std. Train	std. Test
ANFIS (black-box)	0.0056	0.0751	0.0170	0.1149
PSO (gray-box)	0.0313	0.1203	0.0527	0.1323

Table 4.2: Comparison of different estimation algorithms for Δm_{f_c}

Method	MSE Train	MSE Test	std. Train	std. Test
ANFIS (black-box)	0.0143	0.1198	0.0240	0.1470
PSO (gray-box)	0.1483	0.2913	0.0883	0.1763

The prediction error for fuel consumption and SOC when the ANFIS model has been used are represented in Fig. 4.2 and Fig. 4.3, respectively. Additionally, Fig. 4.4 and Fig. 4.5 represent the correlation of ANFIS and high-fidelity data which all verify high estimation accuracy. It is worth mentioning that in Fig. 4.3, there are two data-points that are not identified by ANFIS. Apparently, these two points have a considerable deviation from the rest of the data, which can be due to the outlier phenomenon that might happen during collecting data. This can happen because of measurement noises and/or numerical deficiencies during data acquisition from any high-fidelity software.

This part of simulation studies intends to conduct a sensitivity analysis to evaluate ANFIS performance for a variety of MFs and also different number of antecedents for fuzzification of the crisp data. To this aim, the Gaussian, bell-shape and triangular MFs with 5 and 7 antecedents are considered. As shown in Table 4.3 and Table 4.4, the Gaussian and bell-shape MFs outperform the triangular type, with Gaussian being slightly superior. This observation might be because of the linearity of triangular MF which abates the interpolation power of rule base inference system. Moreover, the sensitivity analysis revealed

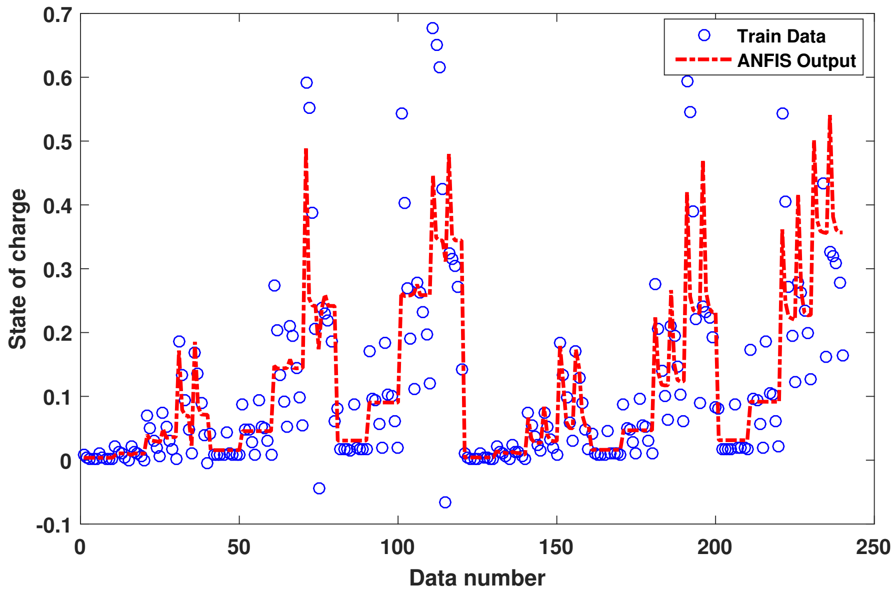

Figure 4.2: ANFIS prediction performance (ΔSOC_c)

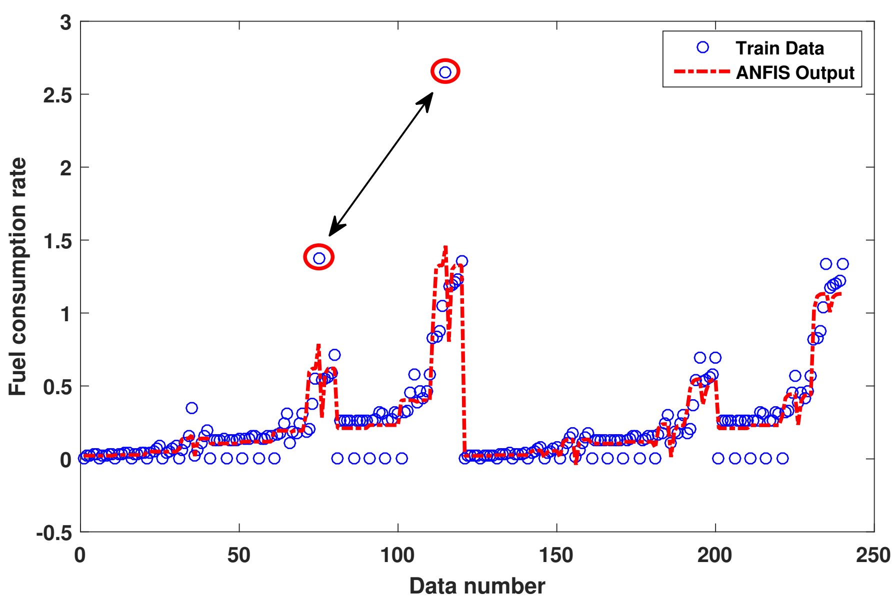

Figure 4.3: ANFIS prediction performance (Δm_{f_c})

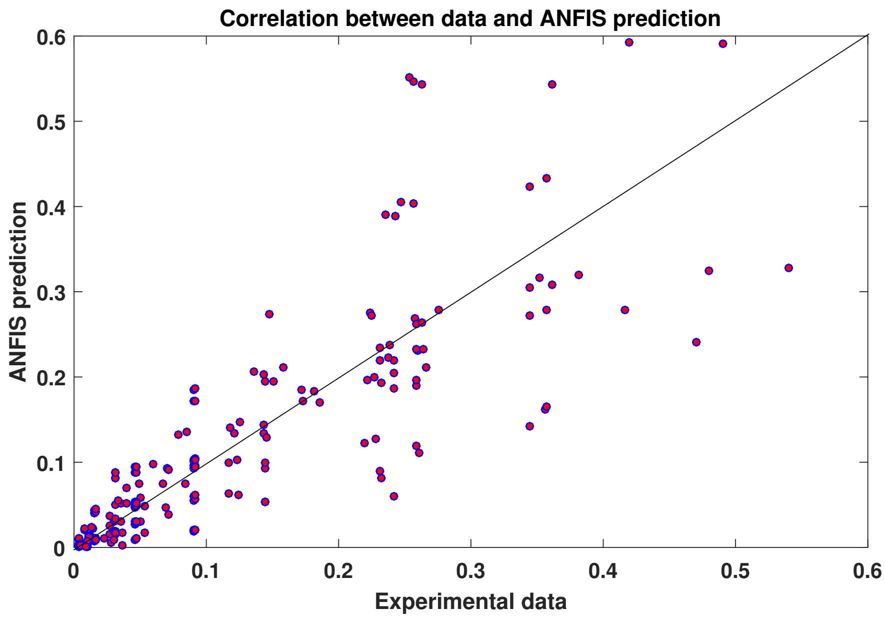

Figure 4.4: ANFIS prediction and data correlation (ΔSOC_c)

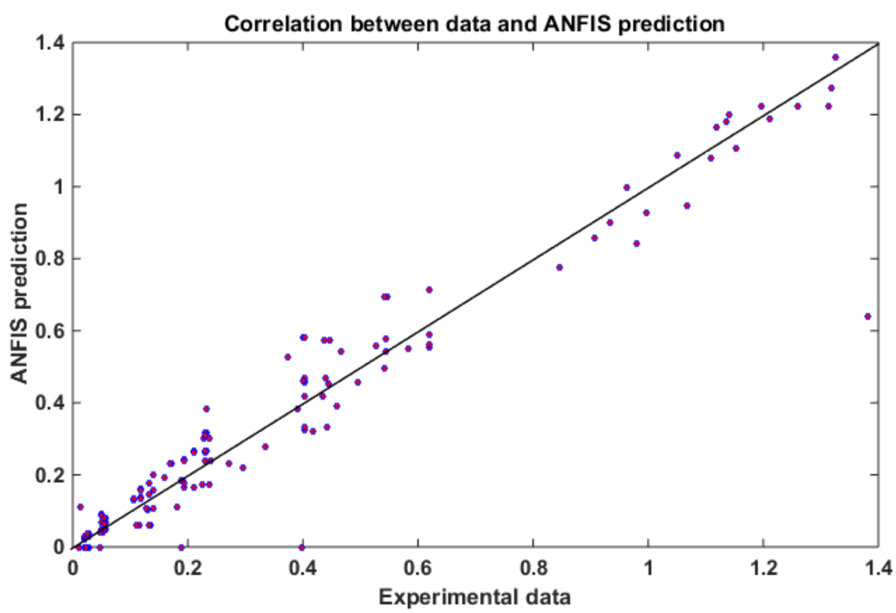

Figure 4.5: ANFIS prediction and data correlation (Δm_{f_c})

that 7 is an optimum number of linguistic rules and more than that can decline the estimation accuracy. Further, a mixture of Gaussian and bell-shape MFs were also examined but it did not exhibit any significant effect on the performance.

Table 4.3: Statistical results of training and testing ANFIS for ΔSOC_c estimation

MF Shape	Number of MFs	MSE Train	MSE Test	std. Train	std. Test
G−G	5−5	0.0058	0.0764	0.0172	0.1157
G−G	7−7	0.0056	0.0751	0.0170	0.1149
B−B	5−5	0.0061	0.0786	0.0187	0.1208
B−B	7−7	0.0057	0.0757	0.0171	0.1153
T−T	5−5	0.0061	0.0785	0.0178	0.1182
T−T	7−7	0.0058	0.0762	0.0187	0.1216
G−B	5−5	0.0061	0.0785	0.0188	0.1210
B−G	5−5	0.0057	0.0756	0.0168	0.1143

G: Gaussian MF, B: Bell-shaped MF, T: Triangular MF

Table 4.4: Statistical results of training and testing ANFIS for Δm_{f_c} estimation

MF Shape	Number of MFs	MSE Train	MSE Test	std. Train	std. Test
G−G	5−5	0.0186	0.1367	0.0295	0.1624
G−G	7−7	0.0143	0.1198	0.0240	0.1470
B−B	5−5	0.0184	0.1360	0.0288	0.1607
B−B	7−7	0.0179	0.1343	0.0280	0.1588
T−T	5−5	0.0194	0.1395	0.0298	0.1637
T−T	7−7	0.0189	0.1378	0.0301	0.1644
G−B	5−5	0.0183	0.1354	0.0286	0.1601
B−G	5−5	0.0183	0.1355	0.0287	0.1603

4.5 Summary

This chapter attempted to investigate the potential application of intelligent techniques in trip planning of PHEVs. A particular emphasis was on the use of PSO and ANFIS to perform gray-box and black-box modeling of energy consumption and in turn evaluate the impact of using such models in SOC prediction. For the gray-box model, the classical empirical model has been used but the parameters - which generally suffer from uncertainties

- were optimized by using PSO. Numerous simulations verified fast convergence, robustness and uniqueness of the solution. For the black-box model, an ANFIS model has been identified and it has been revealed that this model is up to one order of magnitude more accurate than the PSO-based model in addition to being up to two order of magnitude faster in terms of computations.

Chapter 5

Sensitivity/Robustness Analysis

The TP-assisted EMS introduced in the previous chapters has shown to be effective in optimal power distributions between energy sources, rendering significant reduction in fuel consumptions. However, the previous analysis was based on the assumption that the system under consideration is nominal and the trip conditions are deterministic. In practice, there exists a wide range of uncertainties that might affect the control system. This chapter carries out a sensitivity analysis of the TP-assisted EMS to answer this fundamental question: how well the TP-assisted EMS will function in a real-world scenario where unknown measurement uncertainties and disturbances are inevitable?

5.1 Sources of Uncertainties

Before beginning the sensitivity analysis, it is important to identify the major sources of uncertainties and disturbances that can affect the performance of the TP-assisted EMS module.

The input to the TP-assisted module is the prediction of the drive cycle; therefore, uncertainties can be induced to this module from various sources, those that mainly deal with the collection of trip information. Since the drive cycle has a stochastic nature, one immediate source of uncertainty is the poor estimations that might occur during trip prediction. In addition, external disturbances such as wrong traffic light scheduling, pedestrian push-to-walk buttons, sudden pedestrian crossing or abrupt braking of the preceding vehicle introduce a higher level of unpredictability to the drive cycle, not to mention possible failure of connections to traffic monitoring systems. Measurement noise that always exists on sensors such as GPS, radar, V2V, etc. is another unavoidable uncertainty term that is added to the input signal. It is worth mentioning that sensors have limited accuracy; therefore, measurement errors is another source of signal deterioration. Moreover, there can be communication faults during data exchanges which result in momentary information loss.

It is also important to note that the strength of the TP-assisted EMS in suppression of the above uncertainties and disturbances depends heavily on how well the design parameters are being tuned. Therefore, a proper sensitivity analysis requires an additional evaluation of the module's performance for variations of the design parameters. This will provide an understanding of the parameters' impact on the performance and the robustness of the TP-assisted module. With this in mind, this chapter is concerned about a sensitivity analysis with respect to uncertainties as well as the design parameters.

5.2 Monte Carlo Simulation (MCS)

As the TP-assisted EMS decision making is exposed to a significant information uncertainty, it is aimed to investigate uncertainty modeling methods that can work best for our problem. Different ways of uncertainty modeling including probabilistic techniques, robust optimization, interval based analysis methods, etc., have been developed and used in various applications [125]. Basically, the techniques used for expressing the input variables' uncertainty in their algorithms distinguish the methods from each other. As an example, the uncertainties due to trip information is modeled by membership functions to be used within a fuzzy uncertainty handling method, while the probability density function (PDF) is known as the main feature for describing the input's uncertainty in a probabilistic method. Monte Carlo simulation is known as one of the probabilistic uncertainty modeling approaches. Dantzig et al. has carried out one of the first investigations in probabilistic uncertainty handling in 1995 [126].

A probabilistic analysis is formed based on the notion that the input variables are random parameters with known PDFs. Assume that z is a multivariate function of a vector $X = [x_1, x_2, ..., x_m]$ in the form of $z = g(X)$; indeed, X is the input vector of the model with uncertain random variables (e.g. the stochastic predicted drive cycle), function g presents the system model, and z is the output of the system (e.g. the fuel consumption). A probabilistic approach is trying to identify the PDF of z while the PDFs of the random parameters x_1 to x_m are known.

Specifically, the Monte Carlo method uses the repeated random samplings to find the output's performance under the uncertainties imposed to the model through the input variables x_1 to x_m. This method is executed by taking a sequence of steps [127]: first, since each input's PDF is assumed to be known, it is possible to generate a sample, x_q^p, for each input x_q, $q \in \{1, 2, ..., m\}$, by using its PDF. A sample of the output, z^p, is then produced by utilizing the system model as $z^p = g(X^p)$ where $X^p = [x_1^p, x_2^p, ..., x_m^p]$. These steps are repeated for a certain number of scenarios, N_{MC}, to assure that all the possible scenarios are included: $p \in \{1, 2, ..., N_{MC}\}$. Thereafter, a set of stochastic outcomes is produced which can be analyzed statistically by utilizing performance metrics, confidence intervals, histograms, etc. Particularly, in this research, the coefficient of variation, which is defined by Eq. 5.1, is used as the performance index of system's robustness under inputs' uncertainties.

$$cv = \frac{\sigma}{\mu} = \frac{\sigma(M_f^p)}{\mu(M_f^p)} \tag{5.1}$$

where cv is the outputs' coefficient of variation, σ is the standard deviation of the outputs, and μ is the expected value of the outputs. In particular, $\mu(M_f^p)$ and $\sigma(M_f^p)$ respectively represent the expected value and the standard deviation of the outcome fuel consumption, M_f, of the vehicle for all of the scenarios $p \in \{1, 2, \ldots, N_{MC}\}$.

5.3 Scenario Generation

Proper Monte Carlo simulations require samples of stochastic inputs. This work considers two mains categories of samples, one is generated from probabilistic modeling of standard drive cycles, and the other one is real-world driving scenarios.

5.3.1 Probabilistic Modeling

While driving on a straight road, assuming homogeneous traffic conditions, the vehicle speed can be described by a normal distribution, as follows [128, 129, 130]

$$P_G(v; x, t) = \frac{1}{\sqrt{2\pi\sigma(x,t)}} \exp\left(\frac{(v - V(x,t))^2}{2\sigma(x,t)}\right), \tag{5.2}$$

where $V(x,t) = \Delta v$, in which Δ denotes the mean velocity value and $\sigma(x,t) = \Delta(v - V(x,t))^2$ with Δ representing the velocity variance. These two factors of the distribution can be determined in a particular itinerary by using traffic conditions. The standard deviation

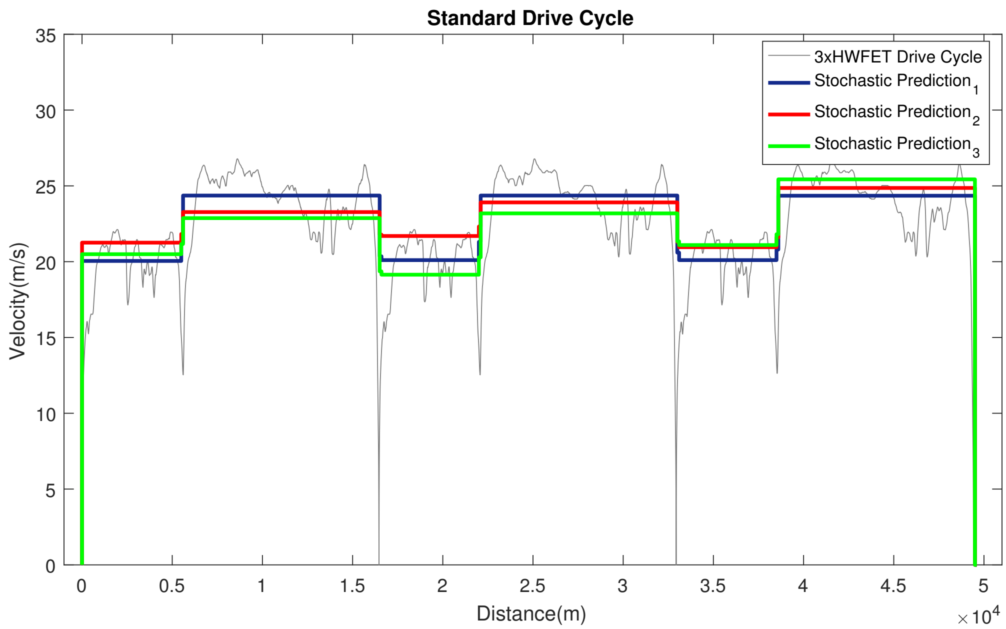

Figure 5.1: Stochastic prediction samples of a given standard drive cycle

of the distribution can be estimated. As pointed out in [131, 132], the standard deviation can be estimated, ranging from 1.4 m/s (5 km/h, near to free flow condition) to 5.6 m/s (20 km/h, near to pulsed condition). In fact, in case of free flow condition, vehicles are moving with a constant speed; thus, a small variance value. On the contrary, the pulsed continuous flow condition is associated with a higher variance value.

For a given standard drive cycle, the samples are generated using the MATLAB *normrnd* function with mean value of drive cycle's speed, $v_{drivecycle}(x, t)$, and the standard deviation equal to $1.4 < \sigma < 5.6$. These samples are fed to the Micro-trip Generator module to generate drive cycle segments, which will be used by the TP module, to evaluate the system's performance under possible mispredictions, while the driver is experiencing the given standard drive cycle in all of the cases. As an example, Fig. 5.1 demonstrates three random segmented samples of 3xHWFET drive cycle.

5.3.2 Real-world Stochastic Drive Cycles

The goal of the Monte Carlo simulations is to examine the effectiveness of the trip planning algorithm against stochastic events that occur during a real-world driving. The drive

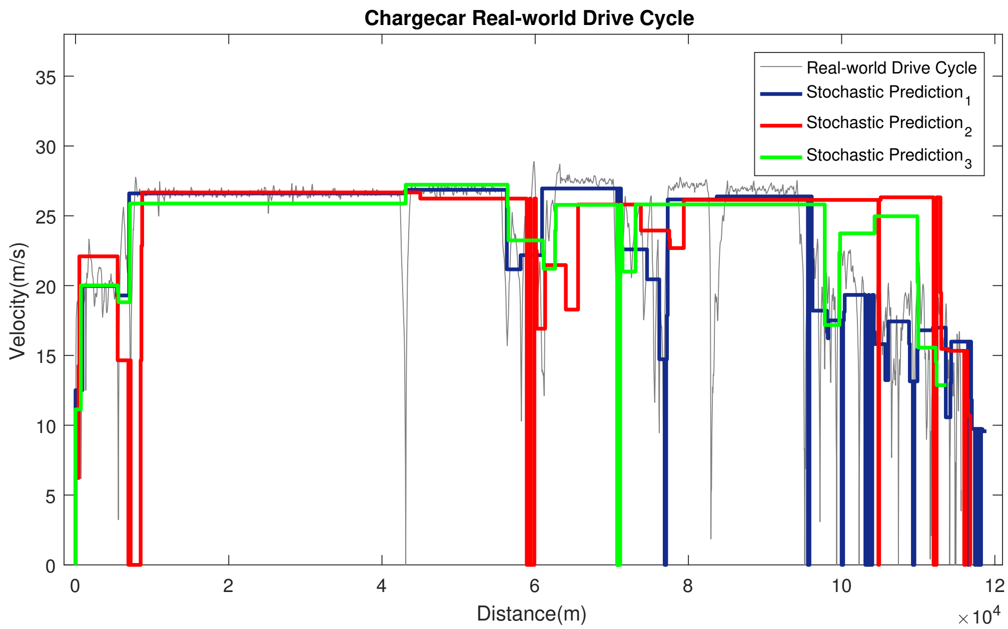

Figure 5.2: Stochastic prediction samples of a given Chargecar itinerary

cycles used in the simulations are real-world scenarios retrieved from [119]. These samples are driving cycles of different routes, each have been driven numerous times, whose the following factors vary randomly:

- Driver
- Travel Time (Day/Night)
- Travel Duration
- Road Conditions
- Weather
- Traffic Type
- Route Type
- GPS Device

By using these samples, the trip planning algorithm will go through real-world scenarios where its robustness will be examined against several stochastic events in a given trip.

Similar to the standard drive cycles, real-world samples are passed to the Micro-trip Generator module in order to segment the drive cycles, which will be then used within the TP module. Fig. 5.2 shows three random Chargecar drive cycles that are segmented.

5.4 MCSs of Trip Information Uncertainties

5.4.1 Different Standard Deviations

In order to evaluate the effect of velocity standard deviation for sample generations, two sets of 1000 stochastic predictions have been generated, using the 3xHWFET drive cycle, one for $\sigma = 1.4m/s$ and the other one for $\sigma = 5.6m/s$. The Monte Carlo simulations are then implemented for both samples, generating the samples of the fuel consumption, whose probability distribution function are depicted by Figs. 5.3 and 5.4, and the MATLAB's $allfitdist$ function is used to fit all valid parametric probability distributions to the data. The statistical metrics of these results are given in Table. 5.1, showing small values for cv in both cases. It is also important to note that the standard deviations of the fuel consumptions are three order of magnitude smaller than the inputs. As a result, upon a large change of standard deviations in the inputs (from 1.4 to 5.6), the TP-assisted EMS exhibits a uniform performance where the standard deviation of fuel consumption changes by 0.0064. This can be verified by the five number summary (minimum, first quartile, median, third quartile, and maximum) plot illustrated in Fig. 5.5. Therefore, the robustness of the system against trip information uncertainties is verified.

Table 5.1: Fuel consumption(L) of two different samples

Sample	$\mu(M_f)$	$\sigma(M_f)$	$cv(M_f)$	$\min(M_f)$	$\max(M_f)$
$\sigma(v) = 1.4m/s$	1.2373	0.0165	0.0133	1.2065	1.2694
$\sigma(v) = 5.6m/s$	1.2291	0.0220	0.0179	1.1787	1.3672

5.4.2 Synthesized Stochastic Samples

To further evaluate the system, different standard drive cycles with a fixed standard deviation $\sigma = 1.4$ is used for Monte Carlo simulations. Note that the previous simulations

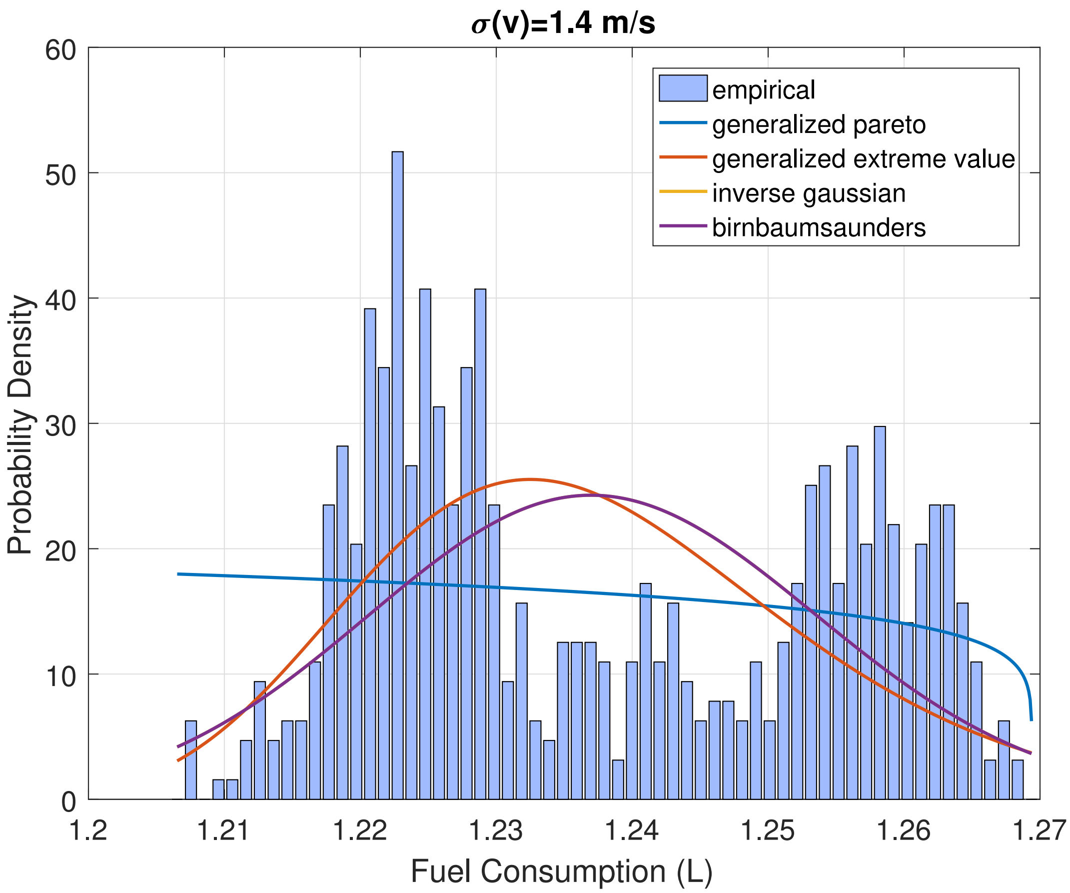

Figure 5.3: PDF of fuel consumption of sample with $\sigma(v) = 1.4m/s$

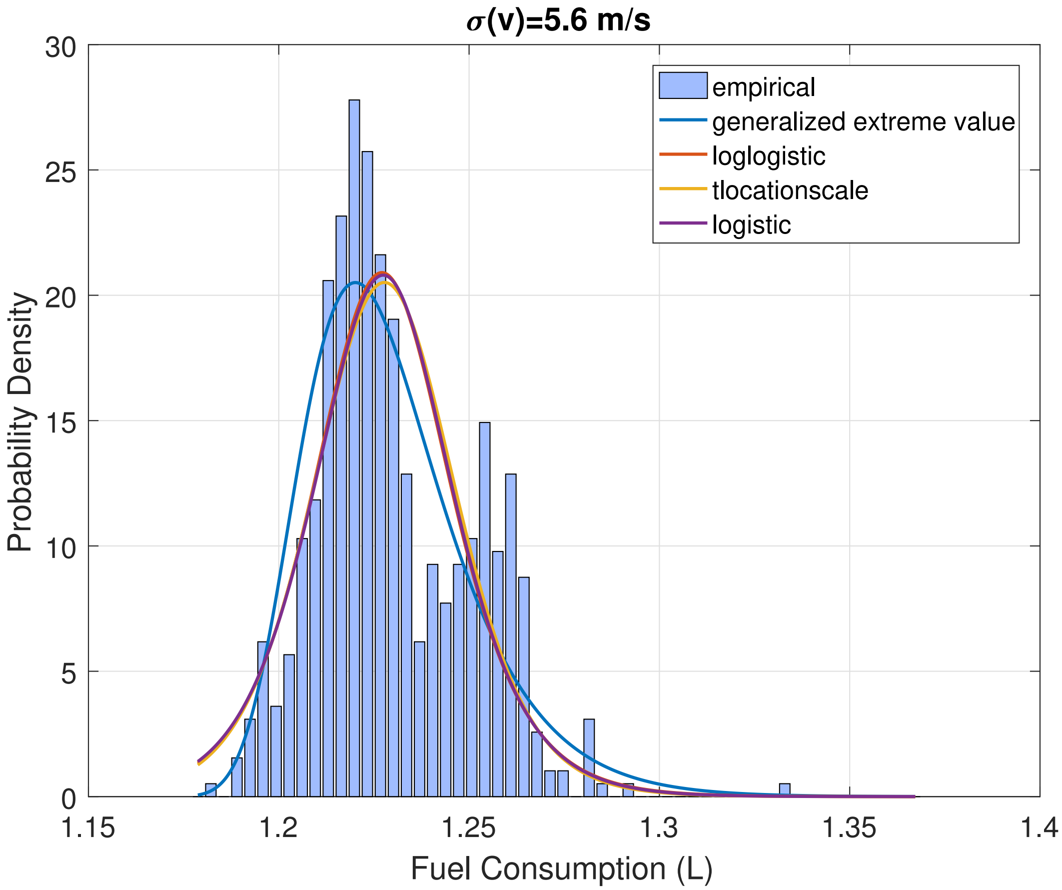

Figure 5.4: PDF of fuel consumption of sample with $\sigma(v) = 5.6m/s$

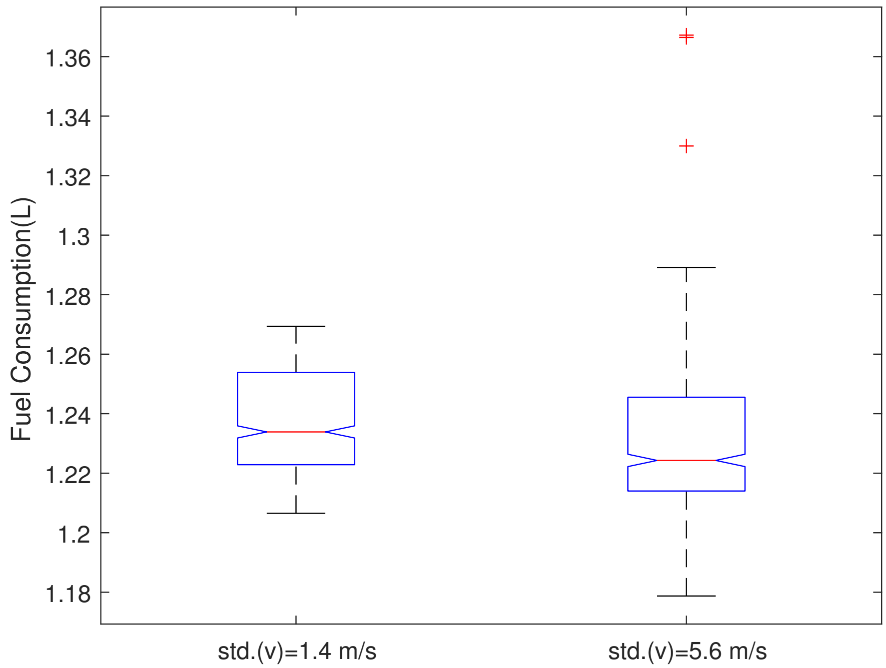

Figure 5.5: Fuel consumption of stochastic predictions for two different samples

revealed that the different standard deviations in input does have a little effect on the output; therefore, similar results are expected if the input samples are generated for $\sigma = 5.6$. Simulation results are presented in Table 5.2 where the cv values are once again found to be small. The results of all the stochastic samples are not far from the actual prediction case, which is the results for a drive cycle that refers to the average of all the samples. Table. 5.2 also compares the Monte Carlo simulation results with the results of A-ECMS and rule-based EMS. It follows that the TP-assisted EMS is a superior method, even for the worst prediction scenario that the TP-assisted EMS has a minimal contribution, the fuel consumption is lower than the other two methods.

5.4.3 Real-world Stochastic Samples

In this section, two sets of real-world drive cycles are used as Monte Carlo input samples. Both itineraries are located in Wisconsin, USA, one set belongs to Milaca, and the other

Table 5.2: MCSs of different drive cycles

Fuel Consumption(MPG)								
Standard Drive Cycles	TP-assisted EMS(Optimal SOC_{ref})						A-ECMS (Linear SOC_{ref})	Rule-based EMS
	Sensitivity Analysis (Sample of Stochastic Drive Cycles)					Actual Prediction		
	μ	σ	cv	max	min			
3xUDDS	108.22	0.3317	0.0031	109.06	107.56	108.27	104.7	97.7
3xSFTP	59.86	0.0833	0.0014	60.04	59.72	60.04	58.4	52.1
2xWLTP	79.01	0.5151	0.0065	79.91	78.41	79.12	78	72.7
EPA_UHU	101.52	0.3354	0.0033	102.10	100.94	102.04	98.3	95.1
3xHWFET	93.28	0.4572	0.0049	94.05	93.01	93.7	92.8	79.3

belongs to Little Canada. The statistical measures of the simulation results are given in Table. 5.3 followed by the five number summary illustrated in Fig. 5.6. As the cv values are small for data sets, it is easy to infer that the TP-assisted EMS presents robustness in real-world driving scenarios when there exist various stochastic uncertainties in the drive cycles.

Table 5.3: Fuel consumption(L) of two different itineraries

Itinerary	$\mu(M_f)$	$\sigma(M_f)$	$cv(M_f)$	$\min(M_f)$	$\max(M_f)$
Milaca	4.2321	0.0058	0.0014	4.2232	4.2450
Little Canada	4.2802	0.0074	0.0017	4.2663	4.2892

5.5 MCSs of Design Parameters Variations

5.5.1 Different Number of Clusters

This section aims to investigate the effect of the number of clusters N_c in the optimization algorithm, as one of the design parameters, on the performance of the TP-assisted EMS. The stochastic samples used in section 5.4.2 are employed for Monte Carlo simulations. Table 5.4 shows the simulation results where small values of cv confirms the low sensitivity of the model against the variation N_c.

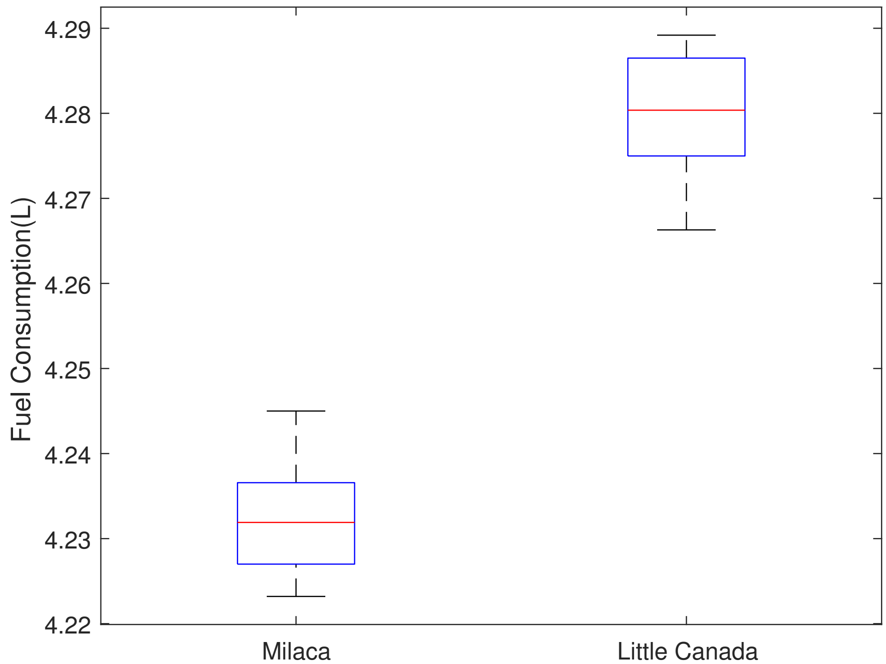

Figure 5.6: Fuel consumption of stochastic predictions for two different itineraries

Table 5.4: Sensitivity analysis for different number of clusters

Drive Cycle	Number of Clusters	Fuel Consumption (MPG)_Sample of Stochastic Drive Cycles					
		Actual	μ	σ	cv	min	max
3xHWFET	4	93.70	93.41	0.4572	0.0049	92.7	94.06
	7	93.76	93.36	0.4621	0.0049	92.74	93.95
	10	93.90	93.52	0.5769	0.0062	92.14	94.08
3xUDDS	4	108.27	108.21	0.3317	0.0031	107.56	109.06
	7	108.15	108.15	0.3433	0.0032	107.61	108.75
	10	108.00	108.20	0.4662	0.0043	107.70	108.99
UHU	4	102.02	101.49	0.3354	0.0033	101.20	102.02
	7	101.58	101.58	0.2689	0.0026	101.07	101.93
	10	101.25	101.34	0.2299	0.0023	100.87	101.68

5.5.2 Different Update Rates

Similarly, for the synthesized stochastic samples in section 5.4.2, the effect of update rates t_{update} in the optimization algorithm is discussed through Monte Carlo simulation. As given in Table. 5.5, the cv values are still small, showing consistent performances of the TP-assisted EMS upon variations of t_{update}.

Table 5.5: Sensitivity analysis for different update rates

Drive Cycle	Update Rate	Fuel Consumption (MPG)_Sample of Stochastic Drive Cycles					
		Actual	μ	σ	cv	min	max
3xHWFET	100	93.70	93.28	0.4572	0.0049	92.7	94.05
	150	93.66	93.52	0.3817	0.0041	92.88	94.01
	200	93.54	93.32	0.4263	0.0046	92.44	93.83
3xUDDS	100	108.27	108.21	0.3317	0.0031	107.56	109.06
	150	107.52	107.99	0.5758	0.0053	106.85	109.16
	200	108.48	108.66	0.3040	0.0028	107.90	109.22
UHU	100	102.02	101.51	0.3354	0.0033	100.94	102.10
	150	101.99	102.17	0.4153	0.0041	101.46	102.80
	200	101.92	101.51	0.7385	0.0073	100.38	102.95

5.6 Summary

The Monte Carlo simulation studies have examined the TP-assisted EMS against various random uncertainties, both in standard and real-world drive cycles, revealing small cv in all scenarios. Moreover, simulations have been carried out for variations of design parameters such as N_c and t_{update}, achieving small cv values again. These verify the repeatability of the TP-assisted EMS which can exhibit high performance in various driving conditions. Equally important, the Monte Carlo simulations showed that in all these random scenarios, the TP-assisted EMS outperforms A-ECMS and rule-based EMS. These are evident enough to conclude that the integration of trip planning with energy management system of PHEVs not only presents consistent performances upon variations of trip conditions and design parameters, but also leads to lower fuel consumptions compared to the existing methods.

Chapter 6

Conclusions and Future Work

This dissertation has concerned with several knowledge gaps related to using trip predictions for proper management of the energy sources in PHEVs which pose formidable challenges in practical usage of this strategy. This idea has been initially proposed by [14] and a pilot study had been presented to proof the concept. However, there was little knowledge on the capacity of the method to be implemented online. Nor was there a comprehensive study on the performance and robustness of this technique in case of real scenarios, where there exist stochastic uncertainties and disturbances. This research attempted to address the above gaps by introducing the TP-assisted EMS module and evaluating its behaviour in various scenarios.

Chapter 3 presented the architecture of the TP-assisted EMS module, which compared to the preliminary design presented in [14], enjoys an efficient PHEV model, namely the power-balance model, which had been derived using first-principles and empirical methods. This model is computationally simple while being sufficiently accurate. In order to speed up of the optimization itself, the PSO algorithm has been utilized. These modifications resulted in reductions of the computation time to below 1 ms, as tested via HIL simulation, verifying the adequacy of the method for online implementations.

Moreover, Chapter 3 presented test results where the performance of the TP-assisted EMS module had been examined in various scenarios and compared to Adaptive-ECMS and Rule-based EMS strategies. The MIL tests carried out for standard drive cycles, hilly road and 60 real-world drive cycles obtained from [119], has verified that TP-assisted EMS is a superior methodology in a sense that it leads to higher MPGs. It is also important to mention that during the experiments, the drive cycles had to processed to be used by the trip planning module. This research has developed the Micro-trip Generator module for this purpose.

Chapter 4 attempted to enhance the TP-assisted EMS module by incorporating soft-computing techniques. In particular, PSO-based gray box modeling and ANFIS-based black box modeling of the energy consumption has been carried out. It has been revealed ANFIS modeling provides more accurate and computationally efficient results compared to the PSO-based one. However, it requires careful considerations in construction of proper learning data sets.

Chapter 5 presented, for the first time, the sensitivity analysis of the TP-assisted EMS module, by using Monte Carlo simulations. In these analyses, the robustness of the module against stochastic uncertainties originating from randomness of the drive cycles has been tested. Moreover, the sensitivity of fuel efficiency with respect to design parameters has been evaluated. All in all, it has been revealed that the module is robust and upon a large change in the standard deviations of the input samples, the standard deviation of the fuel consumption preserves a consistent behaviour.

6.1 Summary of Contributions

In summary, the major contributions of the research can be mentioned as follows:

- Developed the power-balance model for online optimizations performed within the TP-assisted EMS module
- Refined the initial method of energy management using trip predictions [14] and introduced the TP-assisted EMS module
- Verified feasibility of the TP-assisted EMS for online implementations
- Examined the performance of the module and verified it superiority over conventional energy management methods
- Performed Monte Carlo sensitivity analysis of the TP-assisted EMS, for the first time and has shown the robustness of the system against uncertainties and disturbances as well as design parameter variations

6.2 Future Work

The present work can be extended in various directions. One potential way is the model improvement, in particular, the control-oriented model, to take the engine transient states into account. Further, the ANFIS identified model has shown promising performance with regards to accuracy and computational efficiency. As ANFIS inherits the robustness of fuzzy inference systems, it will be valuable to carry out a sensitivity analysis for the ANFIS-augmented TP-assisted EMS module. In terms of the energy management, the current Route-based Equivalent Consumption Minimization Strategy does not account for short horizons predictions. One alternative can be nonlinear model predictive control whose impacts on TP-assisted EMS have not been investigated thoroughly yet.

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