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UNIVERSITÉ DE BOURGOGNE

Effective Simulation Model and New Control Strategy to Improve Energy Efficiency in Hybrid Electric Land Vehicle

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Zainab ASUS

Effective Simulation Model and New Control Strategy to Improve Energy Efficiency in Hybrid Electric Land Vehicle

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Contents

How wonderful it is that nobody need wait a single moment before starting to improve the world.

- Anne Frank

Chapter 1

Introduction

1.1 Motivation

Hybrid electric vehicle (HEV) have two or more propulsion power [1, 2, 3, 4], two or more kinds or types of energy storages, sources or converters, and at least one of them can deliver electric energy [2, 5]. Thanks to presence of reversible energy storage system (ESS) and electric machines (EM) that offer capability of idle off, regenerative braking, power assist, and capability of engine downsizing [6, 7], HEV appears as one of the most viable technologies with significant potential to reduce fuel consumption within realistic economical, infrastructural, and customer acceptance constraints [8].

The idle-off is the ability of the vehicle to turn off its engine when stopped, saving fuel and to turn it back on in a short time when the vehicle starts to move again. The regenerative braking is the ability of the car to recapture a part of the kinetic energy during braking and convert it into electricity to be stored in the battery.

The HEV system has new degrees of freedom to deliver power [7, 8], because ESS gives the possibility to store part of energy produced by engine and use it when needed. Besides that, ESS possesses advantages of zero emissions, independance of crude oil, and low operating cost [9]. On the other hand, EM utilisation covers inefficient operating range of internal combustion engine (ICE) [10, 11] and is designed to handle transient power variations. Therefore, ICE functions mostly at its optimal combination of speed and torque [12, 13] that helps constant ICE operation, offers possibilities in fuel economy, less polluting exhaust emissions [8], and reduced harmful emissions [10, 14, 15]. HEVs decrease emission of greenhouse gases and effect of global warming, and fossil fuel still account 85% of world energy sources and is the least expensive energy source [16].

HEV has great capabilities as new alternative means of transportation [13, 15, 17] for sustainable mobility [4] and as super ultra low emissions vehicle (SULEV) [18]. Research on HEVs became important due to concerns about climate change [14], environment protection [3, 19, 20], stricker legislation for a lower emissions [21], and environmental concerns over urban air contamination caused by black smoke, hydrocarbons, and nitrogen oxides (NO_x of diesel engine buses and trucks) [4, 22].

It is also regarded as one of effective solutions for problem of the energy shortage [4, 21], ever increasing demands on fossil fuel capacity as well as its price [3, 14, 21], and energy conservation problem [20] since it has higher fuel efficiency [19] and can improve fuel economy [8, 9, 10, 12, 14, 15, 17]. HEV possesses better performance compared to conventional vehicles [14, 21]. Nowadays, the trend of electric power consumption has increased and most of the electrical devices replace mechanical or hydraulic components in vehicle and customers expect more performance [21, 23], comfort and safety from this new system [23].

There are many advantages that a HEV system [24] can provide compared to conventional vehicle. In conventional vehicle, the ICE design is heavier, it is sized for peak power demand, its operation at highest efficiency is in a narrow range, its power curve is limited to a band of speed, and mechanical brakes dissipate kinetic energy as heat [12]. But in HEV system, ICE is smaller [12], lighter, more efficient, and sized for average power.

ICE can operate within range of highest efficiency and provide thus greater fuel economy, reduce fuel consumption and air emissions that lead to improvement of human health. This can reduce wear and tear on engine, and also reduce noise pollution caused by low speed engine operation. EM power curve is better suited to variable speed and can provide greater torque at low speed. EM in HEV can recapture part of kinetic energy and store it in batteries via regenerative braking, thus reduce wear on brakes [12].

Eventhough, HEV is regarded as the best solution for the future mode of transportation. It needs so much studies, experiments, and application of simulations for accurate sizing and matching studies, as well as development of control algorithms [8], because control strategy and component sizing do affect the vehicle performance [20]. HEV system has a complex architecture [8], a high degree of control flexibility [10], a complicated power management [10, 20], and it requires coordination of EM and ICE [18] to enhance fuel economy and reduce emissions [4]. Besides that, it results in high initial cost [9, 16] to build a system equipped with a combination of battery, ICE, EM, inverters, fuel cell, or supercapacitor.

HEVs can meet consumers need and has an added value, but its losses of transfered energy should be minimized from source to load [16]. And utilisation of a battery, as ESS, require a long battery charging time and has a short autonomy range [9] because it cannot sustain the whole trip [4] due to battery capacity that is limited to its weight and cost. The engine has frequent starts and stops, and the average efficiency is affected by transients at the starting and ending of its charging cycle [25].

There are great challenges for implementation in energy management and torque distribution. The most important challenge is to meet driver's torque demand while achieving satisfactory fuel consumption and emissions. At the same time, it has to maintain battery SOC at a satisfactory level to enable effective torque delivery over a wide range of driving situations [9, 15]. Compared to conventional ICE system, HEVs integrate more electrical apparatus in its system such as electric machines, power electronics, electronic continuously variable transmissions, embedded powertrain controllers, advanced energy storage devices and energy converters [16]. It has more degrees of freedom that makes its energy management to be complicated and need a deep study before it can be implemented in a real vehicle.

An appropriate energy management strategy (EMS) is necessary to coordinate multiple energy sources and converters [3] and maintain the battery health [4]. The EMS role is to find the most efficient way of splitting the power demand between the engine and the ESS, and decide how to split total power request between sources onboard [4, 7]. So, to obtain maximum energy efficiency, besides of optimising prime mover operation, it has to improve the efficiency of electric components or energy management [23] because improvement in fuel economy depends strongly on its supervisory control strategy [26].

With the problems like global warming, harmful emissions from thermal engines, less fossil fuel ressources, and the fuel price hike, we are still researching for ways to consume effectively the ressources that we still have. But, these ressources will not last for a long time if no efforts are made to slow down the present trend. A development of a new system or a new method takes time to be adapted in an everyday life. With the utilisation of modeling and simulation tools, this can be done quite rapidly for testing and rapid prototyping of a system. And this maybe can allow us to explore new alternative to save fuel. With all effort has been given in all sectors to reduce pollutant emissions and new legislation on emissions of vehicle, HEVs is one of the best alternative to respond well to this expectation.

1.2 Objectives and Scopes

The work will rotates around four terms; hybrid electric vehicle, effective modeling, optimal control strategy, and energy efficiency.

The main objectives of this work is to develop an effective modeling method for an easy deployment of a control strategy, to review and study an optimal control strategy for a specific application, and to analyse improvement that can be effectued to engine for better efficiency in hybrid architecture.

The scopes of this work will include the simulation part of the studied system and its validation with experimental results. Study cases are used to analyse optimization that can be effectued to the original system. The optimization could be a control parameters optimization or a replacement of some components in the system in order to obtain a better system efficiencies through simulation.

Next, a more specific study on the method to improve the original control strategy of the system will be studied. A well established optimization tool will be chosen to optimize the actual control strategy and becomes a benchmark of a new optimal control strategy to be deployed in the system. A method to know energy consumption of the system will be developed in order to obtain an optimal control suitable with the vehicle application.

The main components of the system will be studied for improvements of its energy efficiency. In this work, the system energy sources are converted by ICE and stored in battery. Using the developed model, analysis will be conducted to identify an optimal control strategy for a specific utilisation. Improvements can be considered on certain zone of the engine operational area based on analysis of engine recurrent working points. And, an optimal sizing of the battery packages for another application can be easily found using the model.

1.3 Thesis Organisation

This thesis consists of four main contents besides of the introduction in the first chapter and the conclusion and perspectives in the last chapter.

In chapter two, the overview of the vehicle types and architectures, the modelization tools, and control strategies are presented.

The third chapter presents modelization method of the system and its validation. It begins with a simple method of a quasi-static model and continues with a dynamic model using an Energetic Macroscopic Representation (EMR) method. Then, a replacement of components of the studied system through simulation is presented.

Chapter four explains about the optimization of the existing control strategy and prediction method of the system energy consumption.

And finally, chapter five studies four widely used control strategies in HEV system and the possible improvements through analysis of engine operation and its application to design a better system for other vehicle applications.

Start where you are. Use what you have. Do what you can.

- Arthur Ashe

Chapter 2

Review on Hybrid Vehicles

2.1 Introduction

HEV system is a complex system and it can be built in divers architectures, configurations, and combinations. By identifiying its types and functions, the development of this system can be easily performed and realised. But, HEV system is not just about the physical system, it needs an effective energy management to control the power flow in its powertrain. This is known as the control strategy of the system.

A review on the control strategy that has been employed in developed HEV will be presented in one section of this chapter. This will help us to identify which control strategy is suitable for a specific utilisation and configuration, and which step to take in order to obtain an optimal control strategy that can be implemented in a real vehicle. And finally determining which control is best suited for our developed system.

2.2 Vehicle Types and Architectures

2.2.1 Hybrid Types

A degree of hybridation (DOH) provides a quantitative measure of where power is flowing in a hybrid vehicle (2.1). P_{max_ICE} is the engine maximum power, P_{max_ESS1} and P_{max_ESS2} are the electric storage system maximum power value for the first energy storage system and the second energy storage system and then the following. This helps a designer to decide what type of control strategy to be used and components to be controlled.

$$DOH = 1 - \frac{P_{max\_ICE}}{P_{max\_ICE} + P_{max\_ESS1} + P_{max\_ESS2} + ...} \tag{2.1}$$

Zero DOH designates a vehicle system with engine only and a DOH of one a full electric vehicle like battery, fuel cell, or solar vehicle. In Figure 7.1 each type of vehicles use different portion of energies from various sources depending on its propulsion system. Its application and DOH become a factor to focus the optimisation; on the efficiency or the electrification.

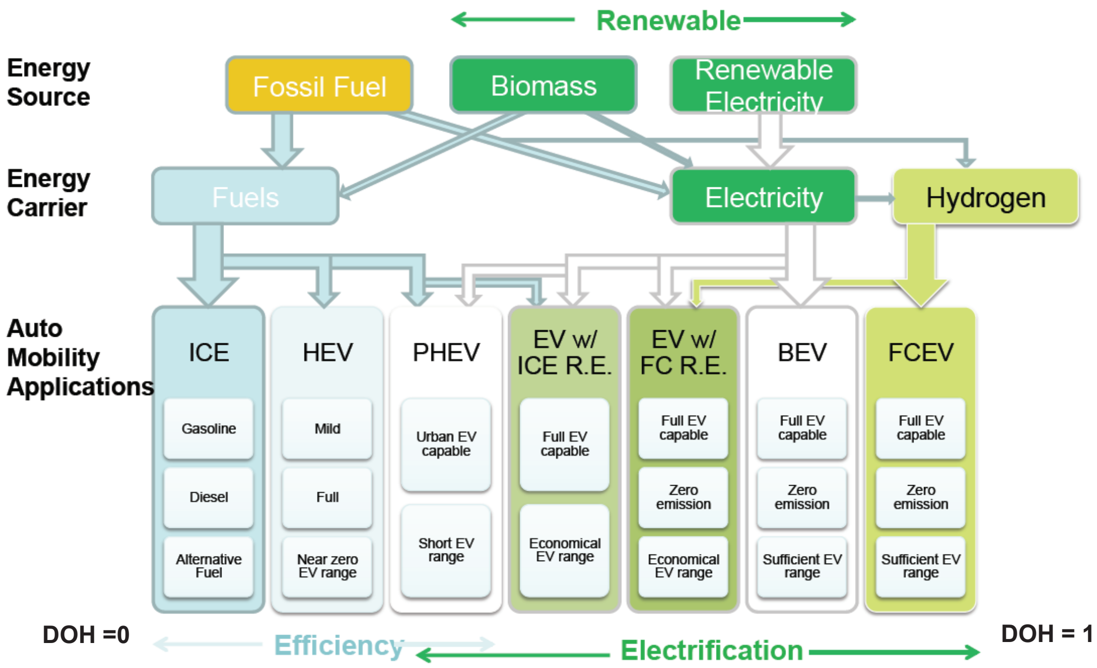


Figure 2.1: Schematic representation of HEV types with flow in power sources and design focus (extract from iTEC 2012 short course on HEV Fundamentals by M. Zhang) [27].

Hybrid Electric Vehicle (HEV)

In automobile, there are different combination of hybrid vehicles, the most common is the engine/battery hybrid, the other hybrids are a combination of components such as battery, fuel cell, solar panel, super capacitor, or flywheel. It is possible that the combination consists of more than two of the mentioned components or combined with the same components like battery/battery hybrid.

The system is complex, it uses electic motor drives and ICE and has battery or supercapacitor as its ESS. It requires only little changes in the energy supply infrastructure, less polluting and has less fuel consumption than ICE vehicle while having the same range. HEVs extend greatly the original EV driving range by two to four times and offer rapid refuelling of liquid gasoline or Diesel [2, 16].

The engine of the HEV can always operate in its most efficient mode, yielding low emissions and low fuel consumption. HEV can purposely be operated as an EV in the zero emission zone.

It is regarded as a practical solution for commercialization of super-ultra-low-emission vehicles. But, HEVs have drawbacks like loss of the zero emission concept and increased complexity [2]. And it has problems of managing the multiple energy sources, battery sizing, and its fuel economy that depends on driving cycle [16].

The three DOH of HEVs are; mild hybrid, power assist hybrid, and full hybrid. The mild HEV is like a conventional vehicle equipped with oversized starter motor to allow the engine to turned OFF during coasting, braking or stop, then to restart quickly. The motor recaptures braking energy and supplies auxillary power.

The power assist HEV has engine as prime mover. It cannot be run on electric power alone and built with reduced size of battery. It needs a big EM to assist vehicle when it needs extra power or for acceleration. The full HEV can run on just the engine, just the batteries, or both. It needs high capacity of battery pack, consequently allows more flexibility in splitting power in the drivetrain [24].

Plug-in HEV (PHEV)

PHEV is equipped with relatively higher battery capacity that can be recharged from external electrical outlet, and can replace fuel by cheaper and cleaner electric grid energy [4, 9, 24, 28]. Therefore, it can achieve a better overall fuel economy and give smaller impact on environment [28]. With a larger battery, plug-in hybrid is capable to run longer in electric only mode [24], take advantage of regenerative braking [29], and sustain an all-electric range (AER) in urban areas [4, 9, 21].

Its technology offers potential of fuel replacement and reduce dependance on crude oil by diversifying energy sources for automobile fuels [30]. It possesses advantages of both system of HEV and EV with small engine that operate efficiently [21, 29], lead to decrease fuel consumption and emissions [9].

However, PHEV needs electric grid charging facilities [16] to access to the power grid through external plug [9]. During AER mode, the electric energy is significantly cheaper, and electric drive trains are more efficient. So, it is advantageous to operate the vehicle in electric mode whenever possible, particularly during transient power demands since ICEs are particularly inefficient during transients, but its performance is trip dependent [21].

State of charge (SOC) is used to describe in which mode the battery will operate, whether in EV mode, charge depletion (CD) mode, or charge sustaining (CS) mode. EV mode is when the vehicle operates in electric only mode using energy from the electric machine only until it completes a predefined cycle or reaches a predefined SOC. The engine will turn on if the electric machine cannot meet the load demands of the vehicle, forcing a mode switch. CD mode is when the vehicle operates using energy primarily from the electric propulsion machine with a net decrease in battery SOC. CS mode is when the vehicle is operating in a manner that the propulsion is powered by the electric machine, the engine, or both, with the constraint of maintaining a constant battery SOC [21].

Commonly, PHEV use grid electricity to power the vehicle during initial driving range, the CD mode and displaces a part of the fuel energy with electric energy [9, 21]. Then, it will choose a blended-mode PHEV control strategy which is complex and multidimensional and will have significant impacts on vehicle performance, driveability, and fuel consumption. The blended mode has less powerful electric drive capability but it can achieve cruise and moderate acceleration in EV mode, but engine utilisation is a must for either higher torque or higher power operations [29].

The engine on-off operation is executed more effectively and efficiently in PHEV. By turning the engine off rather than idle when it is not required for propulsion and turning it on only when the required power is above a predefined value, it can avoid inefficient engine operation. It will not need to start the engine unless the traction battery is depleted. It ensures smooth operation of the vehicle by assigning an engine on and off minimum time interval, because the delay to turn on the engine will increase the regenerative potential of the PHEV and further improve its mileage [21].

Electric vehicle with range extender (EVRE)

Range extender (RE) is an auxillary power unit (APU) attached to a battery electric vehicle in order to increase its driving range. The RE could be an engine combined with a generator, a fuel cell stack system, or other energy sources.

The EVRE is capable to realize AER during initial driving condition, then sustain the charge until the end of a trip. It is equipped with a full-sized traction motor powered by battery causing an increase in system cost. It has a higher power loss at higher power operations [24].

Most of the time the architecture of this vehicle type is in series like the Chevrolet Volt and the Noao racing car.

Electric vehicle (EV)

The definition of electric vehicle goes to a system that transfers electrical energy from its sources to the wheels [16]. Normally, on the vehicle, the necessary energy is drawn from carbon-free energy sources [16], and the system is usually equipped with whether solar panel, battery, fuel cell, supercapacitor, flywheel or combination of those components. Except for a particular fuel cell system that has an on-board fuel processor to reforme methanol to hydrogen. EV system consists of an energy source, a power converter, an electric motor and a mechanical transmission, in which the energy flow can be forward or backward during motoring and braking, respectively [31].

It relies on battery technologies with efficient battery management and motor control systems [18]. The batteries, capacitors and flywheels are energy storage systems in which electrical energy is stored during charging, whereas the fuel cells are energy generation systems in which electricity is generated by chemical reaction. Batteries is the major EV energy source because of their technological maturity and reasonable cost [31].

In the well to wheels point of view, the advantage of EVs on energy conservation is that it offers high energy efficiency with 12.5% crude oil to EV vehicles motion compared to 9.3% crude oil to fuel powered vehicles motion [31]. It can convert the kinetic energy back to electricity through regenerative braking. EVs allow energy diversification from fossil energy sources to renewable energy, or generation of electricity by on board fuel cells. EVs enable load equalization of the electric grid power system during non-peak hours [2, 18, 31]. By recharging EVs at night, the power generation facilities can be effectively utilized the non-stockable energy at this time.

It holds benefit on environmental protection such as gain in air quality, show zero local and minimal global exhaust emissions, operate quietly, and almost vibration-free [2, 18, 31, 32]. To promote EVs, some governments have set aside emission-free zones and have enforced stricter emissions regulations [31]. But, pure electric vehicles have demerits, such as a short driving distance, long recharging time, and high cost, thus it is not a realistic solution for the time being [22, 31].

Eventhough, EVs have improved their performance and made it suitable for commercial and domestic use, it still has not achieved driving ranges as good as conventional vehicles [32, 33]. The development obstacle of EV technologies is the energy sources, in aspect of energy storage and energy generation systems. If EV is composed of only one energy source, the system can only achieve either high specific energy or high specific power. The feature of high specific energy is favorable for long driving range, while the high specific power is desirable for high acceleration rate and hill climbing capability [31].

The most common EV systems are the battery electric vehicle (BEV) and fuel cell electric vehicle (FCEV). The BEV is suitable for small electric vehicle used in short range, low speed community transportation, that will require it to be built with smaller battery size [34]. It is characterized by an electric energy conversion chain upstream of the drive train system that might be composed of battery, ultracapacitor, or solar panel [5, 35]. It features independance on crude oils, high energy efficiency, zero emission, and already commercially available.

The battery is normally recharged from main electricity via a plug and a battery charging unit that can either be carried onboard or fitted at the charging point [36]. Although, it only needs electric grid charging facilities, it has problem in battery and battery management, lack of high performance propulsion, short range autonomy, and has high initial cost [16]. On the other hand, the FCEV has long term potential for future main stream vehicles, however the technology is still in early development stage, and has costs and refueling system as the major concerns. It needs battery or ultracapacitor to enhance power density for starting and acceleration. It is independant from crude oil, has high energy efficiency, zero or ultra low emission, and have satisfying driving range. But, it has issues like high system costs, fuel cell cost, hydrogen production, transportation infrastructure, and fueling system [16].

2.2.2 Architectures

There are three main hybrid vehicle architectures; series, parallel, or series-parallel as shown in Figure 2.2. An architecture that cannot be distinguish within the three classements is considered as complex architecture.

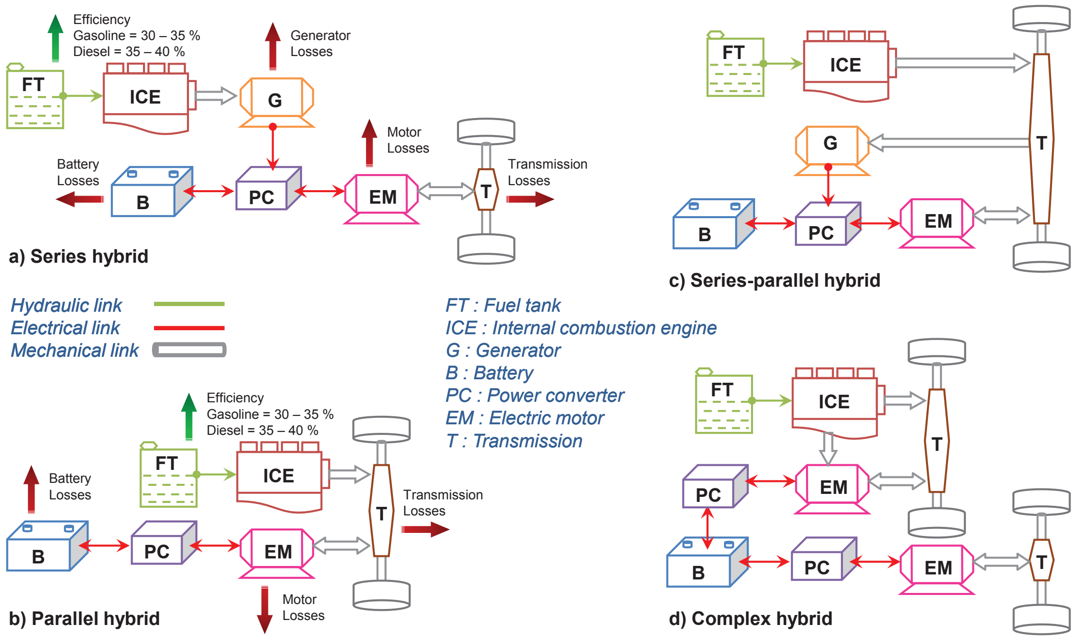


Figure 2.2: Diagrams of different HEV architectures, power flow, and power losses; a) Series, b) Parallel, c) Series-parallel, d) Complex

Series

Series hybrid is the simplest kind of HEV [2] owing to its simple architecture [14] because it has no mechanical connections between engine and wheels [7, 16] as can be seen in Figure 2.2 a).

ICE is not directly connected to the drive train [6, 24], series HEV couples the engine with the generator to first convert the engine mechanical output into electricity for pure electric propulsion. The converted electricity either charges the battery or can bypass the battery to propel the wheels via the same electric motor and mechanical transmission [2, 12].

The power split is between electric generation and electrical storage path [37]. Traction power delivered by EM depends on amount of given battery power for the driving force [12]. ICE does not take part in the propulsion of vehicle, and during light load the excess power is stored in the battery pack [12]. Engine operates frequently at its maximum efficiency point so the fuel efficiency improves and the carbon emission is less than in the other vehicle configurations [16].

The absence of clutches throughout the mechanical link has the definite advantage of flexibility for locating the best operation points of engine-generator set [2]. The speed can be chosen from values corresponding maximum efficiency for a given output power [7]. Due to lack of mechanical link between engine and wheels, series hybrid is efficient in driving cycles that involves many stops and starts such as urban driving [24].

It predominates as an urban transportation, thanks to its outstanding transient performance and power response [14, 16], and is mostly used in heavy vehicles, military vehicles and buses [16]. Other than that, it has advantages such as long operational life and simpler space packaging compared to other architectures that are restricted by mechanical connection between components [16].

This system can operate in two mode; EV and HEV [18]. For a large-sized vehicle applications, series-type HEV have a considerable burden in electric machine size and vehicle weight to satisfy the maximum power rating of the drivetrain [22]. It needs three propulsion devices - the engine, and a separated generator and electric motor [2, 12, 24]. And if it is designed to climb a long grade, all these propulsion devices need to be sized for the maximum sustained power [2].

The larger traction drive system, multiple energy conversions [16], higher operating system voltage and bulky energy storage devices counteract the overall efficiency of this system [12]. But, the engine-generator set can adopt a lower power rating if it is only needed to serve short trips as commuting to work and shopping [2].

Parallel

The parallel hybrid connects directly both power units in parallel; engine and electrical machines to mechanical transmission via drive shaft to propel the wheels [2, 12, 16, 24] (Figure 2.2 b)).

In this system, EM accompanies ICE providing the tractive force and acts as alternator to convert mechanical energy to electrical energy [23]. A parallel HEV can operate in three modes; the propulsion power supplied by the engine alone, by the electric motor alone or by both in hybrid mode [18].

Parallel hybrids do not need a separate generator, because the traction motor can recuperate braking energy or absorb power from the engine when its output is greater than the requested power to drive the wheels [2] and storing them in batteries [12].

This type of hybrid needs only two propulsion devices, a smaller engine and a smaller electric motor [2] because the size and weight of electrical components, such as the inverter and batteries, can be reduced considerably according utilisation [22]. If it is build for long trip operation, only the engine needs to be rated for the maximum sustained power, while only half of the maximum power for the electric motor [2].

Consumers can get the same or better performance as conventional vehicle, unless if the battery is depleted [2]. Parallel hybrid is advantageous in economic gain and has cheaper initial cost compared to other architectures, but the space packaging is complex [16].

Combined or Series-parallel

The series-parallel hybrid is a direct combination of both series and parallel hybrids [2] and combines both features of the hybrid configurations [16].

It inherents advantages from both series and parallel HEVs, has more degrees of freedom in selecting an operating point of an ICE of series HEVs, while having higher efficiency in power transfer and relatively smaller EM than parallel HEVs [10]. But this type of HEV needs an additional mechanical link compared to series hybrid and an additional generator compared to parallel hybrid as shown in Figure 2.2 c) [2].

Series-parallel hybrid incorporates planetary gear set as power split devices that connects two electric machines and the ICE, and allows power path flow from ICE to wheels. The engine is linked to the planet carrier; the generator to the sun gear and the ring transmits the output torque to the differential. The motor is also linked to the ring gear so that it is able to add torque to the output shaft.

Owing to the connection of the sun gear and the planet gears, the speed of the engine can simply be adjusted by varying the speed of the generator. It involves no gear changing, so the engine operation is less transient than the parallel configuration and not as steady as the series hybrid [16].

Although this system possesses advantageous features of both series and parallel HEVs, it is relatively more complicated and costly [2, 16]. The control is complex and it has problems for space packaging [16]. Nevertheless, with the advances in control and manufacturing technologies, some modern HEVs prefer to adopt this system [2].

Complex

This hybrid can offer additional and versatile operating modes. It might be similar to the series-parallel hybrid (Figure 2.2 d)), where the electric motor power flow is bidirectional and offer flexibility in operating modes. Similar to the series-parallel HEV, the complex hybrid suffers from higher complexity and costliness. Nevertheless, some newly introduced HEVs adopt this system for dual axle propulsion which is parallel with transmission by road [2].

A system of hybrid electric vehicle or electric vehicle possess potentials to be developed as a transportation technology that one day can replace conventional way of transportion. The design path is already available and mass production of this system for particular consumer has increased for the past few years. But, the cost of this system is still high and consumer are questioning the reliability of these systems in terms of security, driving sensation, and fuel economy. Therefore, futher studies and experiments are needed to establish reliable foundation for improvement of these systems. One of the important aspects that will affect the performance of this system is its control strategy. There is so much research that have been carried out relating EV and HEV control method. Through the next section we can see the effort made to modelise the vehicle system and observe how the type and DOH of this system influence the choice of a control strategy and objectives of the energy management.

2.2.3 Energy Sources Used in Hybrid Electric Vehicle Applications

A choice of energy sources used in HEV depends on its application and benefits of their utilisation. Diesel engines are usually chosen for utilisation in heavy duty vehicles such as buses and trucks because its significant gain in reducing harmful emissions. And a lithium-ion battery pack is privileged because it has a bigger power to weight ratio compared to other types of batteries. A list of the conducted researches is presented in table 2.1.

Table 2.1: Researches conducted on HEV system.

Institution	Vehicle	Architecture	Engine	Electrical sources
[38]	Military UAV	parallel	gasoline	Li-ion
[39]	6-wheel UAV		gasoline 9.39 kW	battery 25Ah
[30]	Plug-in midsize SUV	parallel	gasoline 100 kW	Li-ion 23Ah
[28]	Plug-in midsize car	parallel	gasoline 120 kW	Li-ion 21.5Ah
[40]	SUV	parallel	Diesel 80 kw	battery
[22]	Bus	parallel	Diesel 9.420L	battery 70Ah
[41]	Car	parallel	Diesel 1.5L 60 kW	battery NiMH 34Ah
[8, 42, 43]	Navistar truck	parallel	Diesel 5.5L 157 kW	Lead-acid battery 18Ah
[44]	Car	parallel	Diesel 68 kW	battery 6Ah
[45]	Car	parallel	Diesel 1.9L 42kW	Lead-acid 18Ah
[46, 47]	Plug-in mid-size SUV	series-parallel	Diesel 1.9L 103kW	Li-Ion 2.3Ah
[48]	Hyper prototype	complex	Diesel 44 kW front wheel	NiMH 6.5Ah rear wheel
[19]	Military 4WD SUV	series	Diesel 88kW	battery + supercapacitor 1.4MJ
[14, 49]	Bus	series	Diesel 171kW	Li-ion 90Ah
[26]	Bus	series	Diesel 112kW	Li-ion 70Ah
[50, 51]	Car	series	microturbine	NiMh battery 60Ah
[9]	Plug-in sedan	series	microturbine Diesel 30kW	Li-ion
[52]	Nemo HEV	series		battery lead-acid, fuel cell PEM

2.3 Modelisation Tools and Methods

Development in computer technology has lead to an explosion of a computer based modeling to simulate and predict behavior of real machines or systems. Utilisation of simulation has advantages of a rapid prototyping, fast design and implementation of a system, with a less expensive development cost and a reduced development time.

Simulation model can be done by a component only model or a global model. Some models are developed to design a real-time controller of a system. But, a simulation model is invalid without a verification with its physical system. Normally this can be done by comparing its results with experiment results from a testbench or to a hardware-in-the-loop (HIL) installation.

In simulation, three main types of modeling methods exist; steady-state method, quasi-static method and dynamic method. The steady-state model is useful for system level analysis and to assess long term behaviour of the vehicle [53]. Less computation time is required because it neglects all transient states and utilises lookup tables to represent its experimental data [54]. An equivalent dynamic model added to a steady-state model forms a quasi-static model. It is usually used in global optimization of energy management [54]. This approach has been used to develop PSAT [30], ADVISOR [55], and QSS Toolbox [35, 40] for system analysis and design methods of HEV drivetrains.

A dynamic model takes into account transient states and can study large load transients that occur during gear shifting or fast acceleration [53, 54, 56]. The model is more accurate and more complex causing an extended computation time, because it requires precise information on characteristic and environment of the system [35, 53, 57, 58]. It can give in-depth information about dynamic effects of sublevel components and facilitates performance measure to determine effective control laws and the optimum powerplant or driveline combination [57, 58, 59, 60, 61, 62]. Dynamic simulation approaches like Energetic Macroscopic Representation (EMR) [63, 64, 65], PSIM [66], and V-Elph [60] simulation packages are developed using this method.

2.4 Control Strategies

A control strategy is usually implemented in vehicle central controller, is defined as an algorithm, a law regulating the operation of the drive train of the vehicle. Generally, it inputs the measurements of the vehicle operating conditions such as speed or acceleration, requested torque by the driver, current roadway type or traffic information, in-advance solutions, and even the information provided by the Global Positioning System (GPS) [3].

The outputs of a control strategy are decisions to turn ON or OFF certain components, to increase or decrease their power output, or to modify their operating regions by commanding local component controllers [3, 17]. In a HEV system, control algorithms manage power distribution between sources to reduce emissions and fuel consumption [67, 18, 26]. It is difficult to tune parameters that minimize fuel consumption manually. The fuel economy of HEV depends on many design parameters such as component sizes and control strategy parameters [30]. Likewise, the selection of control strategy can affect autonomy range of EVs.

The main objectives of hybrid drivetrain energy management system are meeting the drivers demand for the traction power, sustaining the battery charge, have less startups, cut running cost, and optimization of drivetrain efficiency [50]. A good control strategy should satisfy a tradeoff between them. Recently, achieving smooth gear shifting and minimizing excessive driveline vibrations, known as drivability, are included in the drivetrain control strategy [3].

In HEV system, supervisory controller coordinates power control of the primary energy converter like ICE and the electrical storage system through electric machine [1], so that the power requirement and other constraints are satisfied [14]. It exploits power distribution between power sources to minimize consumption, but its performance depends strongly to the information available [68].

A control strategy can integrate approaches to help in the decision process. The stochastic approach can provide a random but predictable situation. It uses data of repeated road profile if there is no future driving profile available [68]. The pattern recognition tools can help classify driving modes and recognizes driver's driving behaviour based on current and previous driving condition, pattern learning, and proper classification [4, 69]. The prediction of future events can inform and provide data of future driving conditions and road profile to forecast the power demand and determine decision of control strategy. For the real time implementation purpose, dynamic feedback control approach is easy to implement because it is based on the current and previous operation [4].

R. Wang and S. M. Lukic [69] summarize the prediction tools that have been implemented on EV and HEV systems. Three techniques are discussed for the control strategy to predict driving cycle like prediction based on GPS [18, 70, 71, 44, 72, 73], Geographical Information Systems (GIS) [44] and Intelligent Transportation Systems (ITS) [4], recognition based on statistic and cluster analysis, and predictive control based on Markov chain [43, 74, 75, 76].

Prediction based on combined GPS and ITS can reduce uncertainty. The GPS acquires the present driving information such as time, speed, trip distance, slope, acceleration, and deceleration. And the ITS provides road conditions, speed limits, and traffic lights placement. Statistic and cluster analysis utilizes historical data to recognize types of driving cycle (urban, suburban, or highway) to measure power demand. Length and time window are imposed to collect and process the data considering the computational burden and real time implementation facility. To analyse the data, it can use the classification algorithms like Bayesian classifying algorithm, decision tree, rough set theory, fuzzy clustering analysis [15, 77], neural network (NN) [78], and support vector machine. The NN is first trained using known driving cycles to recognize current driving condition and predict near future events. The Markov chain modelizes the power demand and predicts the future driving condition, given the current one.

Three types of driving style are mild, normal, and aggressive driving. The classification and recognition methods could be a set of questionaire, fuzzy classification, jerk analysis by using a driving simulator platform, or a Gaussian mixture models. Studies show an agressive driver contributes to poor fuel economy and propose to allocate less torque demand to avoid fuel consumption due to transient engine operation. There are various methods and approaches to determine decision of a controller. Two main methods are the rule based control strategy and the optimisation method. Further explication on the control strategies that have been developed and published regarding hybrid and electric vehicles can be found in the following sections.

2.4.1 Rule Based Method

Rule-based power management strategy is based on engineering intuition and simple analysis of component efficiency tables or charts [42]. It is easy to implement [4] and effective in real-time supervisory control of power flow in a hybrid drive train [3, 16]. The systems operate based on a set of defined criteria. The goal is to operate the system at its highest efficiency point [21].

The rules are designed based on human expertise and even mathematical models and generally without a priori knowledge of a predefined driving cycle [3]. ICE operating point is controlled as close as possible to the optimal point of efficiency, fuel economy, or emissions at a particular engine speed [21]. The EM is used in replenishing the battery based on measured SOC to compensate difference between the driver power request and the power generated by ICE [3]. It is close to load-leveling concept. If the best efficiency is needed for every instant in time during the vehicle operation, the vehicle operation points will be forced in the vicinity of the best point of efficiency at a particular engine speed [16] and maximizing regenerative potential.

Predefined rules are initially set based on desirable outputs and expectations without any prior knowledge of the trip. Flowcharts and state diagrams are commonly used to represent the power flow of a given driving schedule. Rule-based control strategies optimize the performance of each component individually. However, it is a local optimization which has a major disadvantage of not being able to find the global minimum [21]. The implementation is performed with deterministic rule based method or fuzzy rule based method.

Deterministic Rule Based Method

The deterministic rule based controllers operate on a set of rules that have been defined and implemented prior to actual operation. It utilises instantaneous operating conditions as inputs for the decision-making process [21]. It is heuristic method which is based on analysis of power flow in a hybrid drive train, efficiency or fuel or emission maps of an ICE, and human experiences to design deterministic rules. The rules are generally implemented via lookup tables, to split requested power between power converters [3, 16]. It can easily cause the balance of battery charge highly sensitive to the drivers' driving pattern, service route state, and load conditions

[22].

A supervisory controller is designed by G. Rizzoni et al. [40] to distribute power of the torque demand between the engine and the motor, so that the battery can sustain its charge by regenerative braking or indirect loads from engine. The algorithm of the control is as follow: ICE propels the vehicle if the torque needed is above a specified limit to avoid less efficient operation. The EM provides needed power if it is below this limit. And, if the power needed exceeds the limitations of ICE, the EM will be turned ON. At a suitable operating points, the battery will be reloaded to recover the charge to its initial charge. The simulation result shows fuel reduction and the comparison of efficiency tabulation between the conventional ICE and hybrid case as in Figure 2.3.

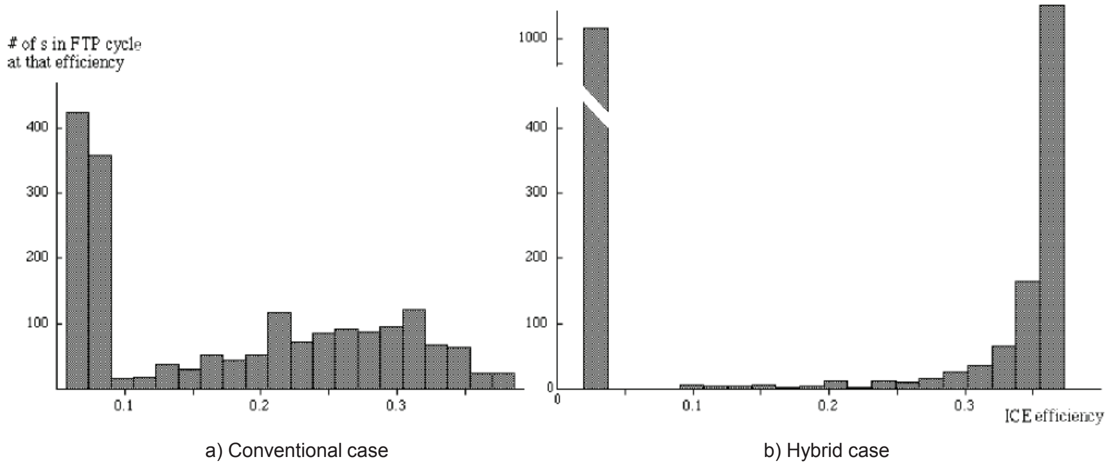
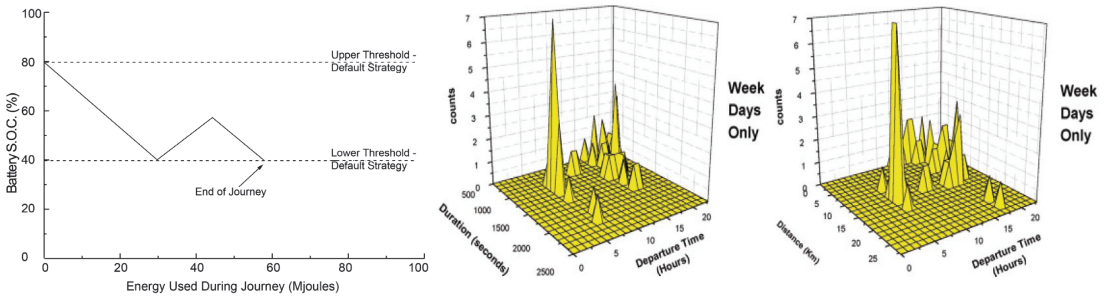


Figure 2.3: Comparison of the ICE efficiencies; a) Conventional case, and b) Hybrid case [40].

A. M. Philips et al. [67] presents the state machine controller to coordinate two power sources of a parallel hybrid vehicle system. The vehicle system controller (VSC) consolidated with a set of ten vehicle operating modes; off, motor drive, regen-low velocity, regen-high velocity, engine drive, boost, charging, engine stop, engine start, and bleed. The three reasons for the transitions to occur are; a change in driver demand, a change in vehicle operating condition, and a system or subsystem fault. Within any particular state, highest priority transitions are associated with system faults. The next priority is the driver demand, except when the system performance is being compromised like low battery SOC. By utilizing the proper dynamic algorithms, a smooth control within and between the states is achieved.

C. Quigley and R. McLaughlin [18] exploit navigation information from global positioning system (GPS) to give good information on vehicle location and routes to reduce EV and HEV system energy usage using estimated journey information. The goal is to minimise the utilisation of ICE by predicting energy requirement and regenerative energy. The SOC is depleted until its minimum threshold before recharged to a level of SOC so that it can complete the rest of the journey in EV mode and reach the minimum SOC at the end of the trip (Figure 2.4 (a)) to reduce emissions, have less startups, cut running cost by using more grid electricity, and have lower net emissons. It allows a second lower limit to complete the journey if the first limit is reached and if it remains a short distance. And, everytime the vehicle want to enter a ZEV zones, it will recharge the battery until upper SOC to have enough charge. It will limit vehicle's acceleration or reduce auxiliaries power to complete a journey without running out of charge. The GPS vehicle location information, departure time and place are used as a reference indicator to predict a near future events. Then it calculates the required and recoverable energy with the road load equation with assumption of no slope and predict patterns of regularly occuring journeys. Week day journeys are predictable, but not on weekends (Figure 2.4 (b)). The duration and energy requirement are repeatable for a regular occurring journeys distance and route information is necessary to be able to estimate this energy requirements more accurately.



(a) View of SOC during a journey under optimized control (b) The relationship between distance, duration and departure time

Figure 2.4: A simplified view of the optimized control; a) View of SOC during a journey under optimized control, and b) The relationship between distance, duration, and departure time [18].

S. Barsali et al. [50] apply thermostat ON-OFF engine control and an algorithm to forecast average power demand (Figure 2.5 a)) in order to maximize the vehicle efficiency while keeping the emissions within predetermined limits to satisfy the required power from the propulsion system (Figure 2.5 b)). It considers desired drive power, road slope, vehicle inertia, accelerator position, forecast information, SOC, and time to fully recharge battery as inputs of the control. The load forecasting approximates future behaviour of the power demand, $P_d(t)$ by exploiting previous values of $P_d(t)$, traffic information, and road slopes. The implementation of the control strategy consider two cases, one by neglecting energy losses in the battery and the other one by taking into account the energy losses in the battery. For the first case, if the forecasted average drive power, P_{fad} is lower than optimum value, P_{opt}, the DC source will be turned ON when it reaches its minimum level and work on its P_{opt}, then turned OFF when it reach maximum battery storage level. In this case, it considers an extra cost due to each startup in form of fuel consumption (Figure 2.5 b)) and lifecycles. If P_{fad} is higher than P_{opt}, the DC source will work as close as possible at its optimal operating points. For the second case, the control considers energy losses in the battery by approximation of a constant $P_d(t)$ on standard cycles. The control forecasts average drive power to deliver power sources (Figure 2.5 c)) and results in reduced consumption.

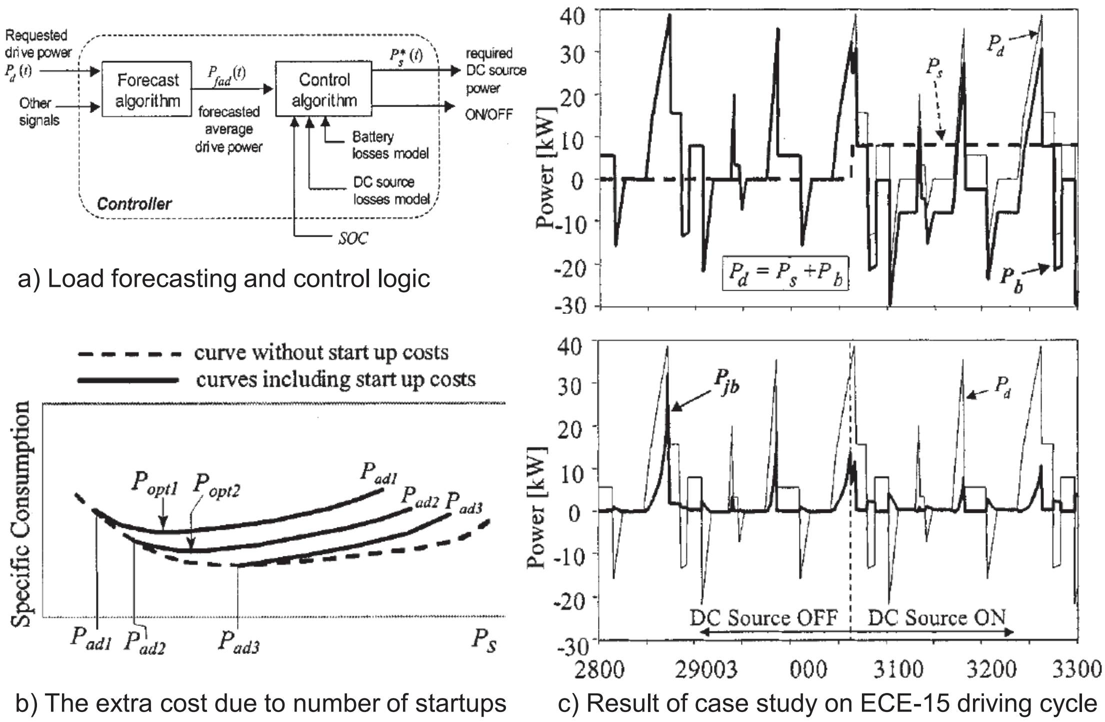


Figure 2.5: The control method; a) Load forecasting and control logic, b) The extra cost due to number of startups, and c) Result of case study on ECE-15 driving cycle [50].

Then in 2004, S. Barsali et al. [51] forecast the average power demand, P_{da} using the historic value power demand, P_d and power request ripple to minimize fuel consumption of a series HEV. The battery operates within two limits, the upper energy limit, E_u at SOC_{max} and the lower energy limit, E_l at SOC_{min} to allow delivery of required peak power and avoid higher battery losses. Its control algorithm updates the required DC source power and decides whether to keep the generator ON, when to turn it ON and OFF, and how much power if it is in the ON state. It considers a fixed amount of fuel, C_{su} for each startup to account for additional fuel consumption and life costs of the prime mover. The instantaneous value of $P_d(t)$ is filtered with T_f, the time constant for the filtering function to be 300 s to avoid improper startup of six different drive schedules. And, it is proven that the chosen T_f value can compensate a wrong choice of journey type (urban or highway). The number of startup is optimal in most of the cases except for a composite cycle of UDDS+HWDS.

J. A. MacBain et al. [55] implement thermostat control strategy to turn ON or OFF the engine based upon battery SOC two set points. The fuel converter will turn on when SOC drops to its lower limit at 75% and will be only turned OFF if the SOC reaches its upper limit at 80%. During this charging event, if regenerative braking occurs, the fuel converter torque will go to zero to capture as maximum energy as possible due to the limited amount of power the battery can absorb at a time. It considers SOC limits, valve regulator set point, DC/DC converter values, and fuel converter operating points as its control parameters. The result shows a realistic simulation for this system to predict fuel economy and performance as in Figure 2.6 under this control strategy.

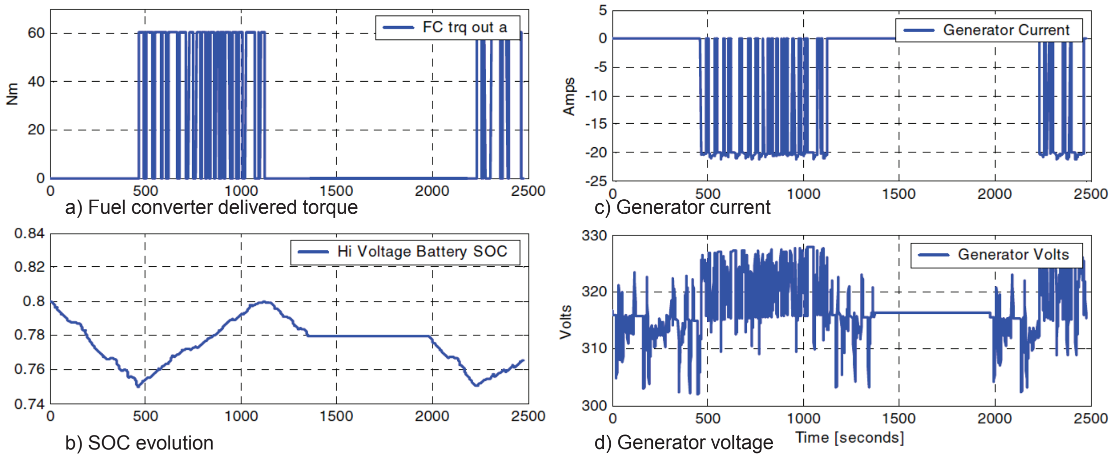


Figure 2.6: Result shows; a) Fuel converter delivered torque, b) SOC evolution, c) Generator current, and d) Generator voltage [55].

Y. Gao and M. Ehsani [79] discuss about the sizing design of an off-road series HEV and its control to reach good vehicle performance such as acceleration, gradeability, maximum speed and travel range in its five operation modes: genset traction, ESS traction, both traction, ESS charging, and regenerative braking. The controller concept (Figure 2.7) of this ESS is an active control, the battery load is controlled in a narrow region for smaller battery design and the ultracapacitor will provide peaking power during acceleration. Also, the ultracapacitor can absorb the peak charging power during regenerative braking. The desired energy power ratio, $R_{\frac{e}{p}}$ is defined by both the components specific energy and specific energy weight ((2.2)). The combination of batteries and ultracapacitors can reduce the volume and weight of the energy storage, improving the battery cycle life, give fast power response, enhance the temperature adaptability, and simplify battery management.

$$R_{\frac{e}{p}} = \frac{W_b E_b + W_c E_c}{W_b P_b + W_c P_c} \tag{2.2}$$

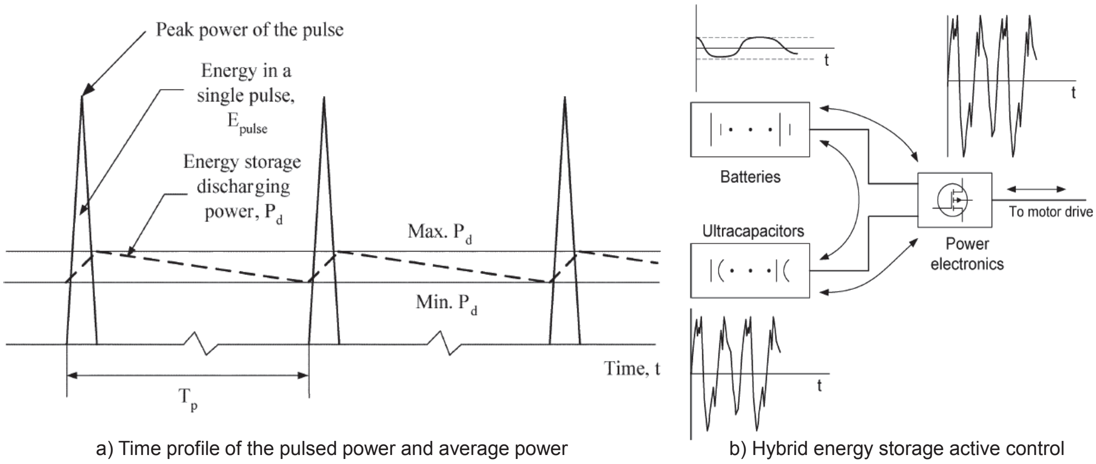


Figure 2.7: Conceptual illustration of; a) Time profile of the pulsed power and average power, and b) Hybrid energy storage active control [79].

M. Gokasan et al. [80] use a control strategy based on two chattering-free sliding mode controller (SMC) to restrict the operation of the engine to the optimal efficiency region Figure 2.8. Two algorithms are developed for a series hybrid control to achieve maximum energy efficiency by determining the generator ON/OFF period and to produce demanded torque when the generator is ON. The engine torque is rewritten as a function of the throttle angle. One of the algorithms is used for the derivation of the battery SOC, maximum power and losses, while the second algorithm makes some forecasts of the system load as shown in Figure 2.9. The developped model is compared with a prototype of a military vehicle and the control strategy is compared to the original PSAT strategy available. As a result, the control strategy allows a larger fluctuations because the engine is controlled in efficient region and it draws power from battery when engine is OFF. However the final SOC is higher and it improves the overall efficiency. Operation points outside optimal region occur less frequently. There are improvement in overall efficiency, engine efficiency, fuel economy and emissions by adding the generator torque control in the 2-SMC strategy.

In 2008, H. Yoo et al. [19] study a system integration and power flow management of a four wheel driven series hybrid military purpose vehicle with three power sources; battery, supercapacitor and engine/generator (E/G) set to deal with military missions. The power flow managements have two operation modes. The normal operation mode begin with a high SOC of ESS, during engine idle, the supercapacitor or the battery will not be recharged until the engine reaches its reference speed or the DC-link voltage is regulated. Once regulated, the engine power reference is calculated based on load power requirement and SOC. During EV mode operation,

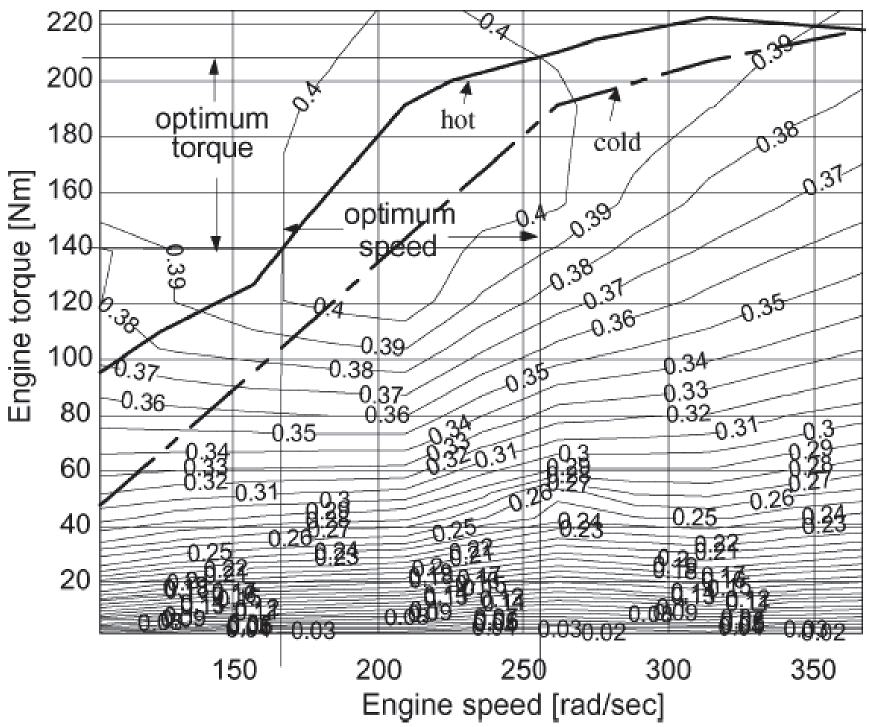


Figure 2.8: Engine efficiency map showing the optimal operating line [80].

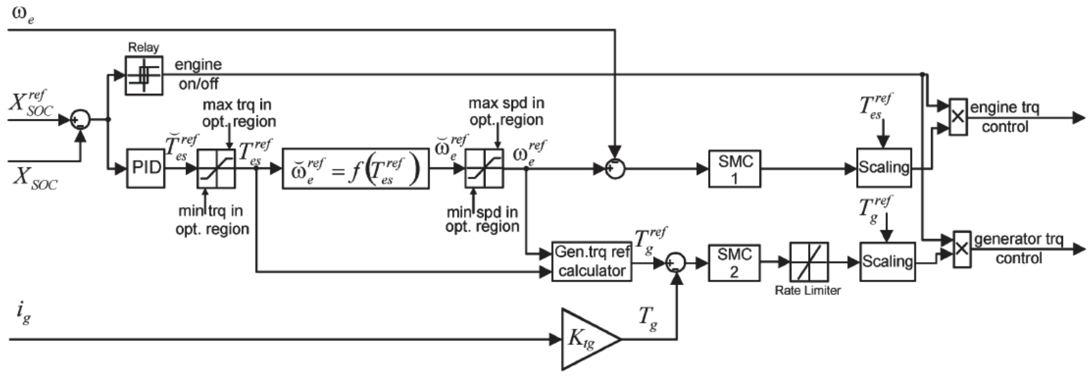


Figure 2.9: The block diagram of the auxiliary power unit (APU) controller based on two chattering-free SMC [80].

the battery will regulate the DC-link and use the supercapacitor to improve the dynamic performance if necessary, by boosting the acceleration and absorbing regenerative braking power. Results from experiments show that the burden of the engine is reduced if the battery supplements power to the DC-link, and the supercapacitor has enhanced the dynamic performance by coping well with power fluctuation.

Then in 2009, H. Yoo et al. [39] propose a power flow control method to regulate DC-bus voltage with the variable speed E/G set, and the battery assists power for rapid load variation. The objectives are to optimise fuel efficient operation, to maximize engine power utilisation, and to regulate stable DC-bus voltage at $\pm 15\%$ of set-point. It controls the speed of the engine and supplies as much power at transient state and steady state. Therefore, the battery lifetime can be increased as well as the power system efficiency. It introduces three battery power reference generation algorithms for the battery to provide supplementary power during rapid increasing load power requirement. Simulation result shows that by implementing the third algorithm of the inversed specific fuel consumption (SFC) map, the engine power increases when the load power increases rapidly, and at the same time the battery provides the supplementary power. The engine outputs its rated power at optimal operating point without degrading desired dynamic performance.

L. Q. Jin et al. [81] analyse control strategies and cost analysis for a plug-in series HEV to use the low price electric energy from grid effectively. The battery working condition is divided into two stages, the charge depleting and the charge sustaining operation. They explain three types of control strategy and finally choose the first all electric range (AER) strategy because it is suitable for a series hybrid system. The AER strategy is a charge depletion operation and then a charge sustaining operation. The other two strategies are based on consumption of both energy sources during charge depletion operation, and are analysed to be more suitable for a parallel hybrid. A simulation in Cruise shows that there is no fuel consumed on the initial range of the driving cycle. Comparison between the cost of this system (1069 Yuan) and a full series hybrid (2526 Yuan) presents a reduction by half of the overall cost per year vehicle use of 16000 km in China.

F. Martel et al. [52] study three recharging scenarios to reduce operating cost of the HEV Nemo and prolonging its battery lifetime. It is equipped with an on-board power sources (PEMFC and ICE) to recharge the battery between intervals of grid power. They develop a battery degradation model in terms of lifetime prediction and performance degradation by using weighted battery capacity in terms of Ampere-hour (Ah) approach. The first scenario, used as reference, is the same operation as experienced by the vehicle in the original battery only Nemo. The second scenario is by adding intervals to recharge the battery on the power grid. And, the third scenario is similar to the second scenario, with additional recharge from ICE during use. The total cost is the lowest on the third scenario with an expected battery lifetime of over 3 years.

M. Sorrentino et al. [72] implement a new rule-based (RB) approach to manage energy flow in a hybrid solar vehicle (HSV) in order to determine ICE on-off scheduling. The HSV battery can be charged during parking hours so that it can restore the initial SOC by end of the day and not by end of single driving path. The external task is to define the desired final SOC_{up} at end of each trip to capture a maximum solar energy during parking. And the internal task is to estimate E/G average delivered power and average traction power produced by SOC deviation ($dSOC$) of battery. These tasks rely on information of daily solar energy, $E_{sun,day}$ and the average traction power, $\bar{P}_{tr}$. The start-stop strategy is described in Figure 2.10. It assumes the SOC did not vary with time, initial SOC_o equals to SOC_f. The E/G will be turned ON if $SOC_{lo} = SOC_f - dSOC$, and will be turned OFF if $SOC_{up} = SOC_f + dSOC$. This step will be repeated until the end of the cycle. The energetic constraints $SOC_{up} + \Delta SOC_{pv} < 1$ is imposed to allow solar energy recharging by ΔSOC_{pv}. The control relies on the current SOC level and the prediction of traction power demand over a trip with application of GPS information or model-based forecasting tool. To ensure a safer battery operation and reducing battery losses, the E/G works based on equation $P_{EG} = g(\bar{P}_{tr})$ to have a lower charging power at low power demand and $P_{EG,opt}$ at high road loads. The simulation demonstrates a significant performance of RB to maximize energy saving through HSV, but this performance decreases in aggressive driving schedules. The RB implements time horizon prediction, t_h model for on-line use and shows low dependence on precise knowledge of future driving conditions. Besides that, simulations to assess the impact of irradiation level on HSV fuel economies demonstrate higher contribution by solar energy in urban driving.

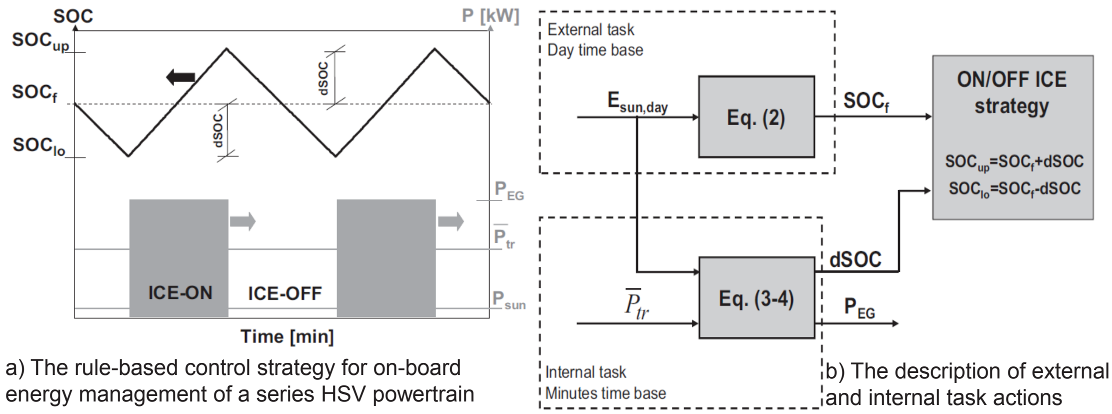


Figure 2.10: Schematic representation of; a) The rule-based control strategy for on-board energy management of a series HSV powertrain, and b) The description of external and internal task actions [72].

B. Zhang et al. [29] design a control strategy for a blended mode plug-in HEV to deplete the ESS to minimum SOC (where charge sustaining mode begins) from full charge of 1.0 to 0.3, by end of vehicle travel distance. It determines the engine turn ON threshold and motor power based on power demand. This power demand is calculated based on a constant vehicle speed, the electric system loss characteristics, the total battery energy, and the vehicle trip distance. The system is built in PSAT as parallel plug-in hybrid of sport utility vehicle (SUV). The control strategy referred as optimal power strategy, utilises the electric power to drive the vehicle until reaching a threshold power demand, P_s. Then, it turns the engine ON to meet desired output power, P_o together with electric system power from motor. A constant mechanical power $P_{em} = P_c$ is maintained while engine running until the end of the drive cycle as depicted in Figure 2.11 b). The method compares the simulation results of this proposed control strategy with an AER control strategy and discovers better fuel savings as the power demand increases, especially if it involves a higher power demand in transient drive cycles. The implementation of this control strategy is feasible in real world application, since it requires information on the trip distance and the battery energy content only before the trip. It can meet high power demand in aggressive cycle and perform better in a longer trip distance than AER.

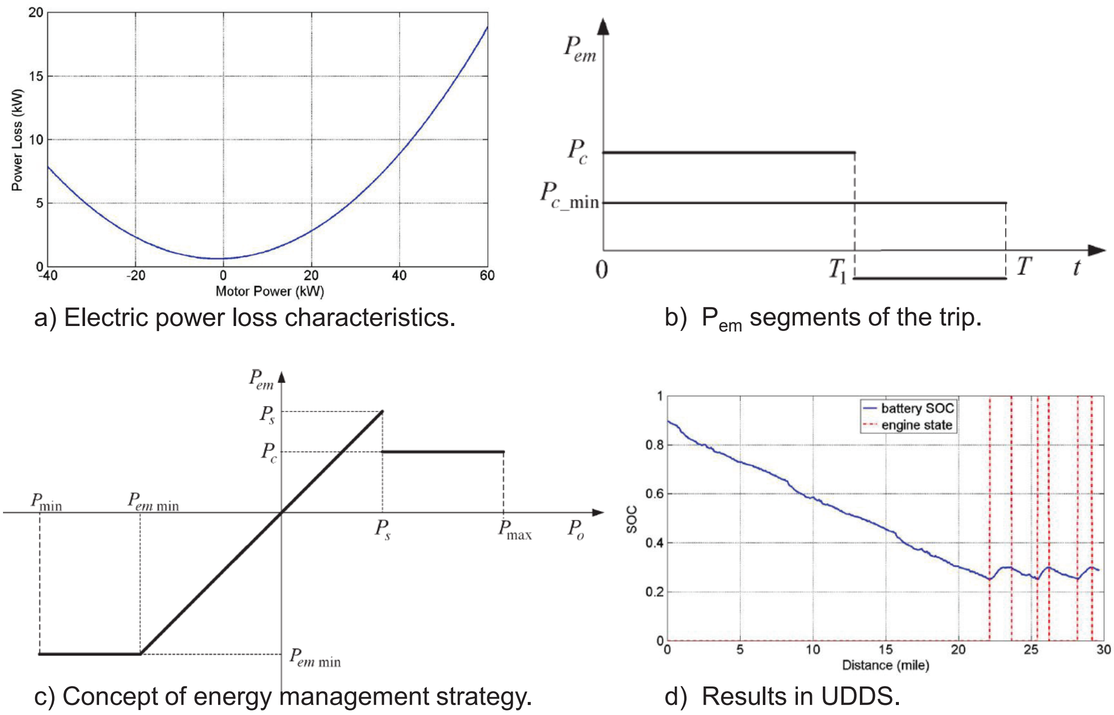


Figure 2.11: Illustration of the control strategy method; a) Electric power loss characteristics, b) P_{em} segments of the trip, c) Concept of energy management strategy, and d) Results in UDDS [29].

Fuzzy Rule Based Method

The fuzzy rule based controllers are ideal for nonlinear time-varying systems, such as a PHEV drive train [1, 21, 16]. Fuzzy logic controllers are computationally efficient [7] and provide a higher level of abstraction to the controllers [21]. Looking into a hybrid powertrain as a multidomain, fuzzy logic seems to be the most logical approach to the problem. It is effective to solve HEV drivetrain complexity problems via heuristics and human expertise [15]. It can be adopted to realize a real time and suboptimal power split [3].

The advantages of fuzzy rule-based methods are the robustness, since they are tolerant to imprecise measurements and component variations [22, 3, 21, 7, 16]. It is adaptable to variations as the fuzzy rules can be easily tuned, if necessary [3, 16]. Fuzzy logic is useful for decision making of an uncertain and imprecise plant, it is not required to fix the precise critical points. The linguistic states of the plant are converted into linguistic control values [22, 7]. Fuzzy rules based control divides the actual driving conditions into different scenarios [4]. Decisions are determined by sets of fuzzy rules by abstraction value of parameters, as fuzziness is a characteristic of human thought and clasification, which is straight forward and intuitive [1]. However, the designed rules are limited to designers knowledge of the system. And they are case sensitive and sometime difficult to tune [39, 7].

H. D. Lee and S. K. Sul [22] propose a control strategy to extend battery life and have easy maintenance of a parallel HEV bus system, which will not result in excessive battery discharge and external recharge. The fuzzy logic control is used to balance the battery charge because it is easy to implement, and need no fixed precise critical points on the speed and acceleration pedal stroke. The logic generates the torque command factor based on rules for the torque and battery recharging control. The results of the proposed strategy, D and E tests are compared to those from deterministic method in A, B, and C tests (Figure 2.12). The final battery charge balance in tests D and E are the same as initial value. And, there are 20% reductions of NO_x emission for the same vehicle performance and power produced, thus confirm the superiority of this control strategy.

B. M. Baumann et al. [1] use a method of load leveling to force the ICE to act at or near either its peak point of efficiency or its best fuel use at all times and the EM power contribution is limited by the SOC of the battery pack. Whenever the torque and the engine speed are too low, the gear ratio and accelerator will be increased to maintain a constant ICE power output and the EM will operate as generator to absorb the excess torque. The distribution of this power is made by fuzzy logic controller to assign an element not only to a set, but more or less of that set depends on its degree of membership throught a membership function. The method considers three inputs; desired power (accelerator and brake pedals), SOC, and EM torque to determine the ICE torque and engine speed (Figure 2.13).

The Intelligent energy management agent (IEMA) consists of two parts. In [15], R. Langari and J. S. Won describe the first part of the IEMA that incorporates driving situation identifier to identify roadway type, driving style, and current driving mode and trend to enhance performance of the vehicle. This IEMA is integrated in a fuzzy logic based torque distribution and SOC compensation strategy (Figure 2.14). It identifies driving situation with its four identifiers. The

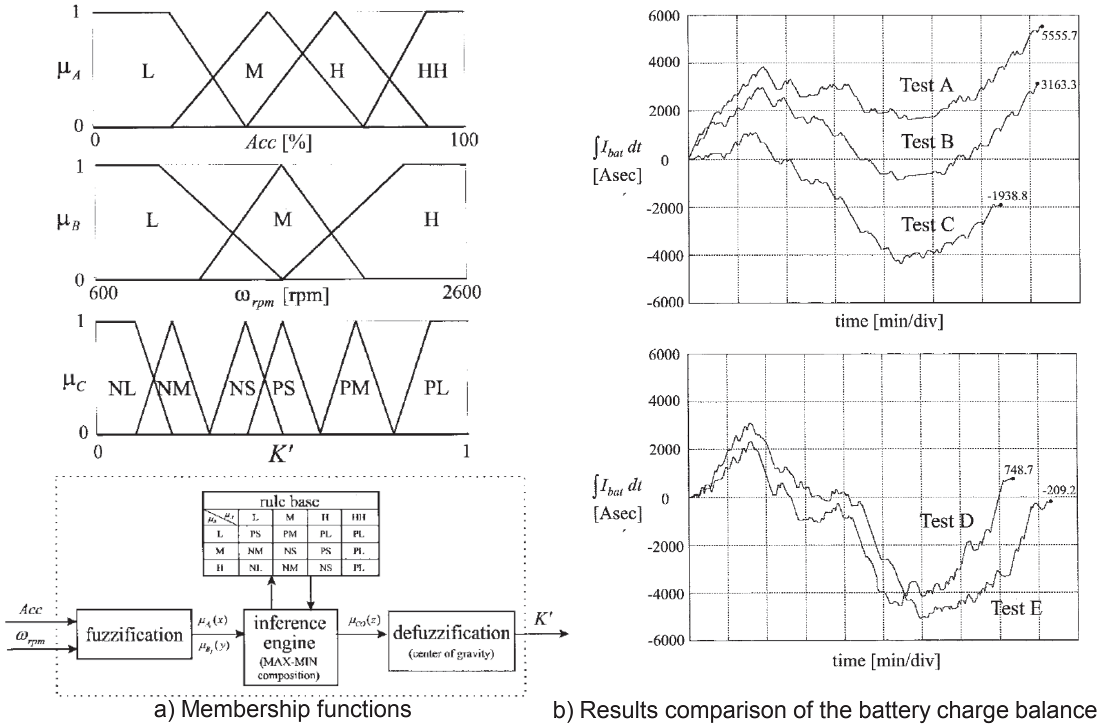


Figure 2.12: The fuzzy rules control strategy; a) Membership functions, and b) Results comparison of the battery charge balance [22].

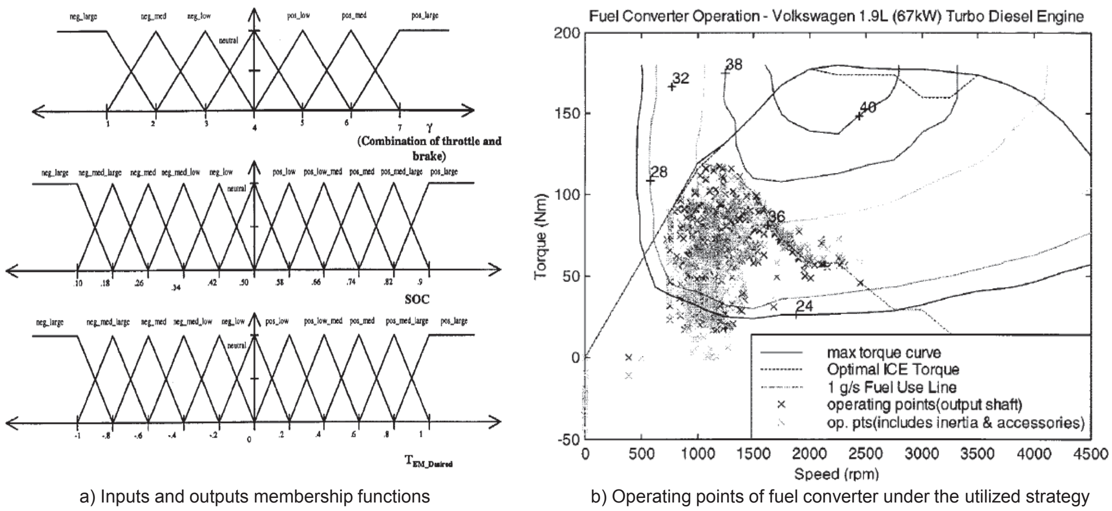
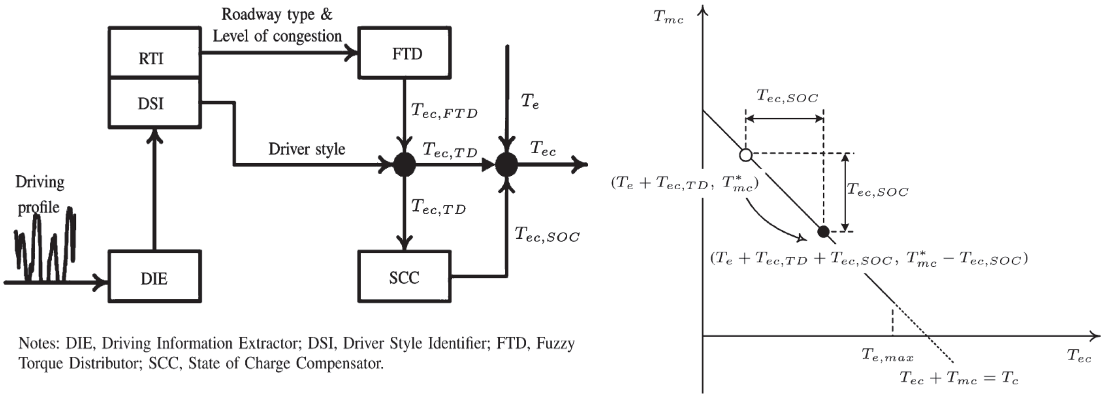


Figure 2.13: Fuzzy logic controller; a) Inputs and outputs membership functions, and b) Operating points of fuel converter under the utilised strategy [1].

driving information extractor (DIE) determine the roadway type, driving style of the driver, driving trend, and characterize the driving situation. The driving situation identifier (DSII) incorporates the roadway type identifier (RTI) to classify the current traffic situation in terms of roadway type and traffic congestion level, driver style identifier (DSI), driving trend identifier (DTI) to assess short term or transient features of a drive cycle, and driving mode identifier (DMI) to determine the current vehicle's operating mode. The fuzzy torque distributor (FTD) determines the effective distribution of torque between the motor and the engine. The state of charge compensator (SCC) extends driving range capability and guarantee the battery charge sustainability throughout the journey. It implements learning vector quantization (LVQ) network for RTI. The DSI identifies types of driving style such as calm, normal, or aggressive driving because it is implied that it can affect the emissions rates and the fuel consumption.

In [77], J. S. Won and R. Langari explain the second part of the IEMA for the driving situation identification unit, then torque distribution and energy sustenance strategies by establishing a facility of roadway type based fuzzy rule sets. It also establishs operating modes of the strategy, the hybrid mode and stop mode for the charge sustenance task. The goal of this control is to minimize fuel consumption and pollutant emissions by operating ICE at its efficient region and avoiding transient operations such as abrupt acceleration/deceleration and frequent stop-go. Three out of six of the membership functions are to assess driving trends, two to assess driving modes and the last one to assess the SOC. There are three facility specific rule sets: the low speed cruise trend, high speed cruise trend, and acceleration/deceleration trend. The SOC compensator (SCC) detects the current SOC to compare it with the target SOC and comprises four different operation modes: battery charge operation, charge sustaining strategy in hybrid mode, and in stop mode, and vehicle mode based charge operation in hybrid mode. The SCC task is to detect the current SOC and compared it with the target SOC, and commanding whether additional or subtractive torque from engine current torque is required (Figure 2.14). Results from simulation show that the RTI is effective in classifying the roadway type, but if the DSI and DTI are off, the fuzzy rule functions with only the DMI. The overall performance of this system can be improved under IEMA supervision.

M. H. Hajimiri and F. R. Salmasi [71] proposes a control algorithm that takes into account the future path information from GPS to generate a control signal. The predictive algorithm (PA) uses fuzzy logic controller (FLC) to predict the vehicle future state, in order to improve the fuel consumption, emissions, and performance of the vehicle. Then, it modifies the approach to extend battery life by considering its state of health (SOH), known as predictive and protective algorithm (PPA). The FLC's first input is the difference between the predicted future speed and the presently measured speed. And the second input is the difference between the future elevation and the present vehicle position. The FLC outputs the battery charging and discharging reaction towards the future state. More battery energy will be consumed in a slower traffic and higher elevation. And, it will be discharged at present if the future traffic is smooth and has decreasing



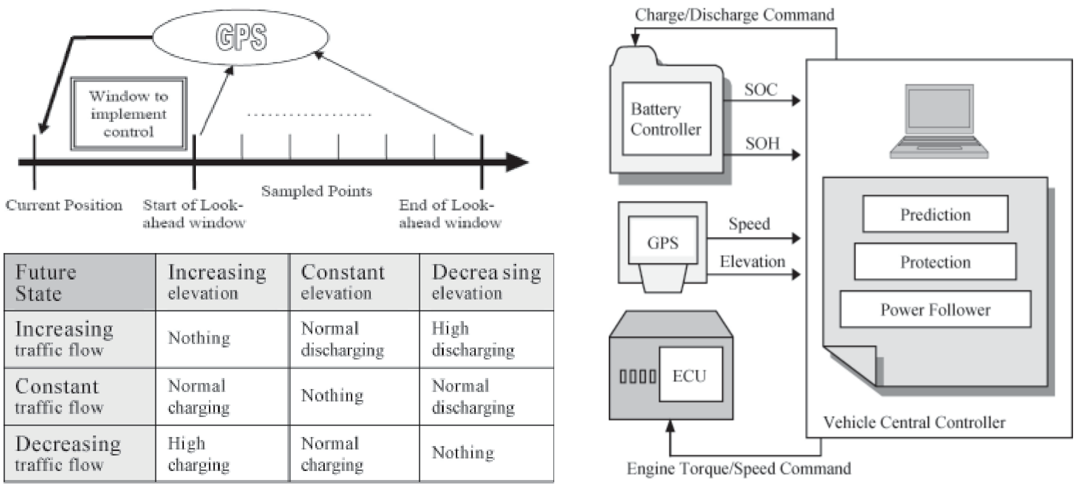
a) Driving situation identifier (DSII) b) Illustration of the charge sustenance operation

Figure 2.14: Architecture of IEMA; a) Driving situation identifier (DSII), and b) Illustration of the charge sustenance operation [77].

elevation. Comparison of results between the power follower algorithm (PFA), the PA, and the PPA show a lowest fuel consumption and emissions for the PA. The PPA which considers SOH as its third input has a slight increase in fuel consumption and emissions compared to the PFA. Because, the PPA intends to limit the battery maximum peak current and the number of battery recharge cycles to improve battery SOH condition, thus lower battery power and use of more power from engine.

In 2008, the same authors [82] have modified the power follower energy management system of a series hybrid electric vehicles to extend battery life, consider emission reduction along with prolonging of batteries lifetime. Optimisation by minimization of a new cost function (2.3) in function of capacitance, resistance, voltage, charge, and current is made to obtain charging current profile in order to decrease charging time and improve the battery lifetime. The control algorithm known as power follower, operates engine/generator (E/G) intermittently to avoid low output range operations with poor efficiency or emissions. A fuzzy logic controller is used as the predictive and protective control by acquiring future vehicle's path and SOH of battery respectively. The predictive controller considers two inputs; the difference between present and predicted future speed of the vehicle, and the difference of the elevation of the future and the present vehicle position. A GPS acquires the knowledge of the obstacles that will be faced in the near future, such as heavy traffic, or a steep grade. It has better tracing capability for areas with variable road elevation. The rules are based on fuzzy logic to determine how the vehicle should react to the future states as in Figure 2.15. The protective controller inputs are the same as predictive controller, in addition of SOH. This approach proves that it can reduce charge/discharge cycles during an interval and the SOH may restrict battery charging and discharging pattern. However, it may increase the emissions and sacrifice fuel economy to extend battery life, if the SOH is in a critical condition. But, this is considerable because battery is an important and expensive component of this system.

$$J = \int_{0}^{t_t} \{(V_{Cb_{max}} - V_{Cb})^2 Q_1 + (C_{b,max} - C_{bulk})^2 + I^2 R\} dt \tag{2.3}$$



Future State	Increasing elevation	Constant elevation	Decrea sing elevation
Increasing traffic flow	Nothing	Normal discharging	High discharging
Constant traffic flow	Normal charging	Nothing	Normal discharging
Decreasing traffic flow	High charging	Normal charging	Nothing

Figure 2.15: The concept of the predictive and protective control strategy [82].

In 2008 X. Liu et al. [83] design a fuzzy logic controller for a series hybrid electric campus and gymnase bus, to keep the SOC working in a high and reasonable range (0.7) to provide a relatively long electric range. Its aim is also to operate the engine in its high efficiency area to minimise fuel consumption and emissions. When the SOC reaches the lower limit, the engine will be turned ON until it reaches the SOC higher limit. And, to avoid over discharge of battery, the engine turns ON if the power demand is high enough. It sets a minimum shutoff time to prevent the engine turns ON frequently. It considers 4 inputs; SOC, ΔSOC, ΔP, and the variable output, k. The controller is simulated through 5 times UDDS cycle, and shows the evolution of different $SOC_{initial}$ that eventually become 0.7. The consumption is higher if the $SOC_{initial}$ is lower than 0.7, and vice-versa to achieve the constant SOC_{final}.

Then, in 2010 X. Liu et al. [84] use a fuzzy logic control strategy (FLCS) to regulate power of a series hybrid bus, and maintains its SOC at high level and reasonable range (0.6-0.8) to provide a relatively long clean range in electric-driving only mode at any time. It maintains the SOC at expected value of 0.7. Using 5 times UDDS driving cycle, the FLCS realizes constant SOC control quickly and steadily to 0.7 for the off-line simulations. Then, it implements ant colony algorithm (ACA) to find power sequence to obtain a longer driving range with a low fuel consumption as its optimisation algorithm. For this purpose, the engine/generator set output power can possibly be 0 kW, 7.5 kW, 10 kW, 12.5 kW, and 15 kW. The resulting sequence depends on the predefined driving range, if the distance is long, the sequence will be composed of higher APU output power. Comparing result to a thermostat control strategy, the vehicle has a longer driving range for a same amount of fuel consumption after optimization.

A. Poursamad and M. Montazeri [85] propose a genetic fuzzy control strategy of a parallel HEV to minimise consumption and emissions. The fuzzy parameters of membership functions are tuned offline using genetic algorithm (GA) (Figure 2.16). The driving performance is imposed as the constraint of the penalty function. The control strategy determines how to distribute the drivers' required torque between the ICE and EM. If torque request is positive, the sum of the engine and motor torques should be equal to the drivers' torque request. During braking, the sum of the motor and brake torques would be equal to the drivers' request. It is aimed to minimise fuel consumption and exhaust emissions (HC, NO_x, and CO) but these goals often conflict each other. Besides that, it is to maintain and enhance the vehicle performance like gradeability and acceleration. Another constraint is to sustain the charge by forcing the SOC to recover to its initial level by the end of a driving cycle. Moreover, it also considers the engine torque limits, motor torque limits, and battery power limits as constraints.

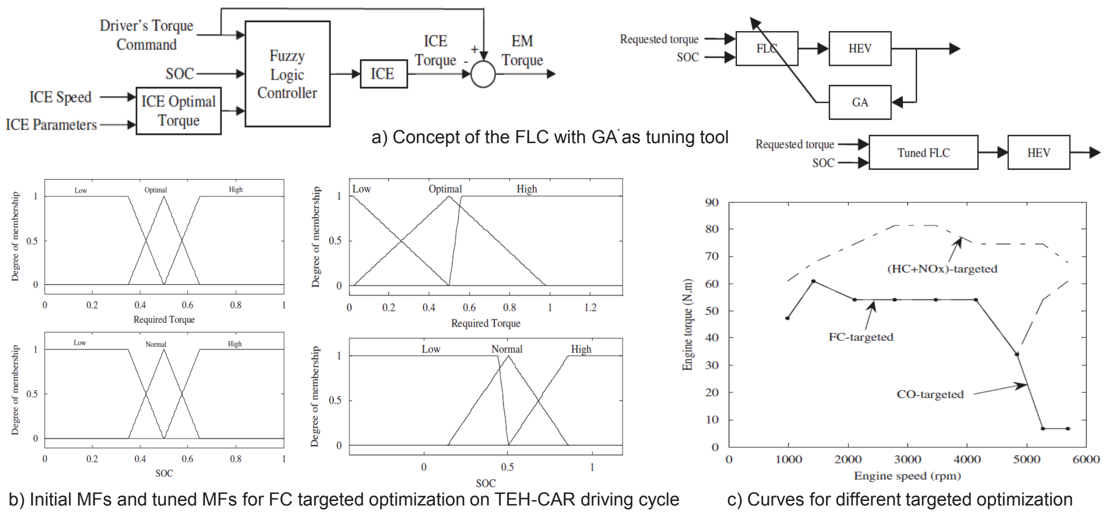


Figure 2.16: The fuzzy logic controller (FLC); a) Concept of the FLC with GA as tuning tool, b) Initial MFs and tuned MFs for FC targeted optimization on TEH-CAR driving cycle, and c) Curves for different targeted optimization [85].

F. U. Syed et al. [86] propose a dynamic model of a power-split HEV system to operate the engine at its most efficient point by managing power and coordinating operation state of components to meet driver's demand and provide the desired energy. During EV mode, the vehicle is propelled by electric motor only. Then, during positive split mode, the generator will transfer engine power output to drivetrain, and the electric motor varies according to power demand and engine/generator (E/G) response. When the vehicle is in parallel mode, generator provides zero power, hence motor torque depends on engine torque output. In negative split mode, the electric motor compensates power from generator instead of using power from engine to improve fuel economy. The model presents reasonable accuracy and predicts the power train response with reasonable accuracy and has a relatively high degree of fidelity and can therefore be used as tool to develop advanced HEV control systems.

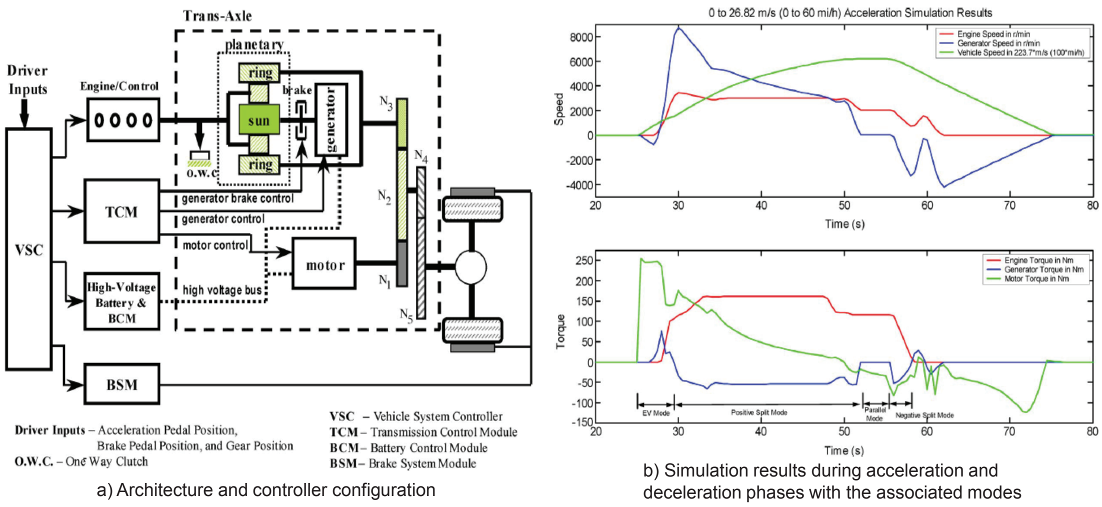


Figure 2.17: The system; a) Architecture and controller configuration, and b) Simulation results during acceleration and deceleration phases with the associated modes [86].

The same authors develop a fuzzy control approach adaptable to nonlinear behavior, in order to control engine power and speed behavior in a power-split HEV system in [87]. It uses selective minimal rule-based fuzzy gain-scheduling to determine appropriate gains for a proportional-integral (PI) controller based on the system's operating condition to reduce overshoots without compromising system's response and settling times. It determines desired speed, ω_{eng} and torque, T_{eng} for engine operation under all conditions by evaluating the driver's power request, P_{req} and desired high-voltage (HV) battery power, P_{batt}. The inputs like accelerator pedal position, brake pedal, and the vehicle speed is calculated as P_{req}. P_{batt} is determined based on battery SOC and environmental conditions. During hybrid mode operation, P_{eng} is calculated based on feed-forward engine power, P_{engff} and HV battery feedback power, P_{battfb}. It utilises a multiple-input single-output Mamdani fuzzy gain-scheduling based PI controller. It compares experimental results using this strategy with a classical PI controller resulting minimum overshoot in ω_{eng} which is reduced from over 600rpm to less than 100rpm. This smooth engine speed behavior gives an acceptable and approriate vehicle drivability to driver. And, it shows no deterioration in the engine speed rise time.

Furthermore, in 2009, F. U. Syed et al. [88] utilise fuzzy logic to split power of a series parallel HEV system efficiently. They use a fuzzy gain scheduling and a nonlinear proportional integral approach to control engine power and speed behavior for better performance and maximum total efficiency. The fuzzy gain schedule acts as a tool to determine appropriate gains for the PI controller based on the systems' operating conditions. Different from conventional PI controller which only calculate the battery feedback power, the desired engine power is calculated as the sum of desired feedforward engine power and battery feedback power (Figure 2.18). The control strategy global stability is verified through extensive simulation and experiments. It results in a fast rise time of the actual engine power. Battery power of a classical PI controller winds up in imposed test conditions and results in engine speed and power overshoots, but this PI controller can control unnecessary winding of its integrator. The fuzzy controller can ensure that the actual battery power did not went below 0 kW during transient event, can enhance response and controllability and provide smooth engine speed.

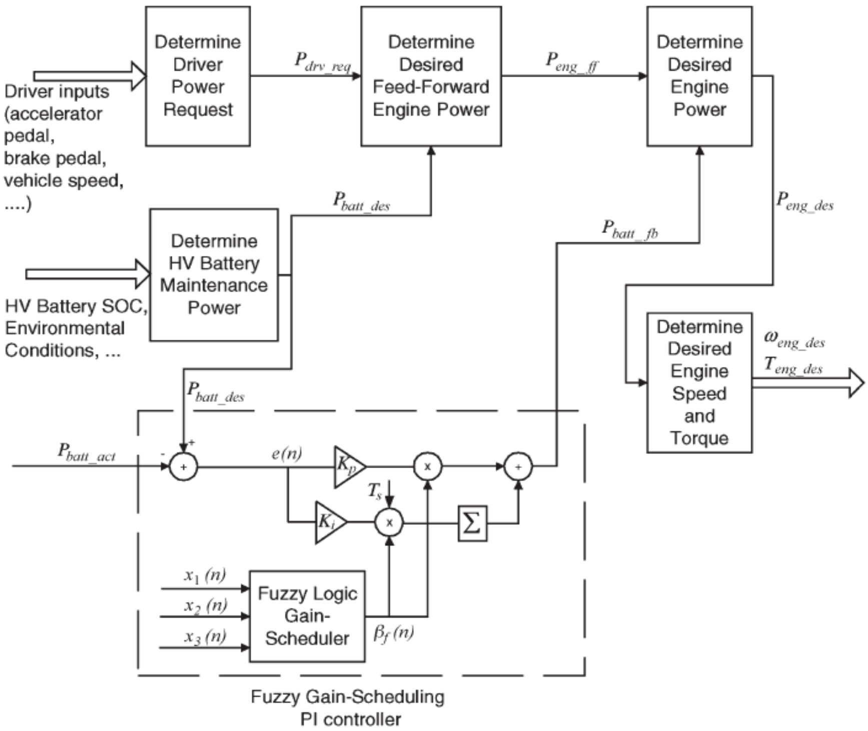


Figure 2.18: Illustration of control strategy decision process and the fuzzy rules [88].

2.4.2 Optimisation Method

The optimisation based control methods can be local, global, real-time, and parameter or threshold optimisation. They can provide generality and reduce heavy tuning of control parameters [48]. Optimization based controllers main task is to minimize a cost function. This cost function is derived based on the vehicle and component parameters and the performance expectations of the vehicle [21]. Optimisation of overall system takes into account the efficiencies of all devices and determines power distribution of each system [25]. Normally, these control strategies intend to maximize the efficiency of the powertrain while minimizing the loss [16]. Optimization also provides the ability to incorporate two variables, mileage and emission goals, as one cost function that can be optimized [21]. The optimal reference torques for power converters and optimal gear ratios can be calculated by minimization of a cost function generally representing the fuel consumption or emissions [3, 16]. Having accurate trip information and component conditions is vital in developing an optimum controller. Technological advances such as the GPS, internet maps, and real-time traffic data have made trip planning a simpler task [21].

The optimisation control strategies use numerical and analytical method to optimise the system operation globally or instantaneously. The numerical methods for global optimisation assume that the knowledge of the entire driving cycle is known and find the global optimal control numerically, by using dynamic programming (DP), genetic algorithm (GA), or other algorithms to give optimal solution, but it is not implementable in real world application. The numerical methods for local optimisation consider a short-term extending into the future, to enable it to be implementable for online, but it will require a large computational capabilities, predictive tool, stohastic DP, or statistical methods to predict the future driving cycle. The analytical optimisation methods consider entire driving cycle and use analytical problem formulation to provide an analytical formulation that makes the numerical solution faster, but sometime it risks to over simplifying the solution. The example of this method is Pontryagin's minimum principle (PMP) and Hamilton-Jacobi-Bellman equation [7]. The instantaneous minimization methods minimise cost function at each time step, for example the equivalent consumption minimisation strategy (ECMS) has demonstrate result close to the global optimum [4].

Global optimal controller can find a global optimum solution over a fixed driving cycle, but it is noncausal [3, 89]. Global optimisation needs to know future driving conditions or scheduled driving cycle, and is not suitable for real time control [48]. It needs heavy computation requirements and is therefore difficult to apply for real-time control and is usually used for offline simulation applications [3, 14, 21, 16]. However, it might be a basis of designing rules for online implementation or comparison for evaluating the quality of other control strategies. It is a good design tool to analyze, assess, and adjust other control strategies [3, 16]. In HEV system, it can search solutions to achieve performance targets by optimization of a cost function representing efficiency and emissions over a drive cycle, yielding to global optimal operating points using knowledge of future and past power demands [16].

There are various algorithms that can yield global optimal solution. Linear Programming (LP) and Sequential Quadratic Programming (SQP) use the derivative information to find the local minimum solution, but it does not search the entire design space and cannot find the global optimal solution. Algorithms such as Direct Rectangle (DIRECT), Simulated Annealing (SA), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO) are non-derivative and can work well for multi modal, noisy and discontinuous objective functions [30].

Dynamic programming (DP) is well known as a benchmark for the performance of other strategies [8, 4, 89] with its global optimum solution [26]. The calculation is based on fixed driving cycle and does not deal with the variability in the driving situation [15]. Dynamic optimization is made within a time horizon, rather than for a fixed point in time [42]. Computational complexity of every DP algorithm is exponential with the number of the states and inputs, thus needing attention to minimize computational cost. DP can solve the optimal control of non-linear, time-variant, constrained, discrete time approximations of continuous-time dynamic models of HEV [89]. It can achieve absolute optimal fuel consumption for different system configurations, but it needs all of the future conditions for inputs to be known a priori [89, 68]. Its not implementable in real world due to their preview nature and heavy computation requirement [8, 42, 26], therefore it is difficult to be applied in real time control [4, 26]. But, it can be used for offline simulations and to compare performance of a real time controller [26]. DP is more accurate under transient conditions, but computationally more intensive. It can be used as tool to analyze, assess, and adjust other control strategies and extract implementable rules, as to improve intuition based algorithm. DP main advantage is that it can easily handle the constraints and nonlinearity of the problem while obtaining a global optimal solution. The overall dynamic optimization problem can be decomposed into a sequence of simpler minimization problems [42] or use two scaled DP to improve computation efficiency [4].

Real time optimisations minimize a cost function at each instant, recognised as an instantaneous cost function that depends only upon the system variables at the current time [48, 3]. This optimization is a causal system that relies on real-time feedback to optimize a cost function that has been developed using past information [48, 21]. The key difference is its ability to optimize itself in real time. It attempts to optimize a cost function [21] by taking into account measures of fuel consumption and SOC deviation [48], but it has limitation on knowledge of future driving conditions and the electrical path self-sustainability [48], because detailed knowledge of the entire trip in advance is not available [10]. This can be solved by adding variations of the stored electrical energy and include it as an equivalent fuel consumption to guarantee electrical self sustainability [3, 16]. Of course, the solution of such a problem is not globally optimal, but this instantaneous optimisation can be used for real-time implementation [3, 14].

The most common method is the equivalent consumption minimisation strategy (ECMS). The advantage of the ECMS approach is that it does not rely on the practically unattainable global future vehicle driving power profile instead only the equivalence factor (EF) when solving the global optimal control problem [9]. Usually, the strategy intend to maximize overall efficiency to reduce consumption and emissions [26]. But, a single value of EF is not suitable for all situations and conditions and needs to be adjusted according to one utilisation. Whereof, application and adaptation tools are needed to estimate the EF best value. The adaptive ECMS can yield EF based on current driving condition but it requires good tuning of parameters, which is depend on current driving conditions, but only suitable for charge sustaining and not for charge depleting strategy [4]. Stochastic approaches can consider a set of driving cycles which are difficult to cover in real world driving situation. The optimisation is possible over a short horizon by prediction of vehicle load in the near future. The performance of the optimisation that implement this approach is directly related to the prediction accuracy. Model predictive control (MPC) approach anticipates upcoming events according to available set of data, but its performance depends on the quality of prediction information and length of the prediction. Trip prediction and modeling approach is facilitated with ITS, GPS, and GIS. It can get information with wireless technology of vehicle-to-vehicle and vehicle-infrastructure interaction, traffic flow monitoring systems, or real time and historical traffic information from roadside sensors [4].

$$J(t,u) = \Delta E_f(t,u) + s(t)\Delta E_e(t,u) \tag{2.4}$$

Global Optimisation

E. D. Tate and S. P. Boyd [90] introduce an application of a convex optimisation that is assumed to be a large linear program (LP) to find a global optimal engine operation in a series HEV. The objective is to minimise fuel consumption over a predefined trip and it can be extended to reduce emissions. This approach is independent from any control law and it finds the minimum fuel consumption with knowledge of past and future power demands. First, the problem is imposed as a convex optimisation problem, then it is imposed as a linear program by converting the problem into discrete time event before casted in a standard LP form. This method is expected to be used for the components sizing requirements purpose and to evaluate a control law performance.

F. G. Harmon et al. [38] build an optimization algorithm that generates optimised instantaneous energy for the system using a nonlinear control surface data that is generated offline. This nonlinear efficiency maps are stored in tables and calculated by interpolation. It has three operating strategies: electric only, charge depleting (allow SOC to decrease to maximize the use of electrical energy) and charge sustaining (attempt to maintain the battery at a target SOC) during flight. It is compared with a rule based controller (with charge depleting (CD) mode, then charge sustaining (CS) mode) of two inputs: demanded torque and rotational speed. The engine is operated on a line of maximum efficiency. The weighting factors penalize the amount of electric energy used and the recharge depends on the missions: CD for short missions and CS for a longer missions.

D. Karbowski et al. [91] develop a Stateflow control strategy to minimise the cumulative energy losses throughout a cycle. It considers two modes: blended and electric only mode. It tries to delay the engine start to maximize regenerative braking energy and reaches the final SOC value of 30% at the end of the cycle with an initial SOC of 90% (Figure 2.19). It uses the Bellman Principle generic algorithm to determine command of the engine torque and gear number. The engine ON time increases with the aggresiveness of the driving cycle. The real time controller is based on two modes: charge depleting and charge sustaining mode. The engine ON pattern is different for the first part of the trip to reach a low SOC, but then it is similar for the remainder of a repeated cycles. The engine is used during acceleration and high speed.

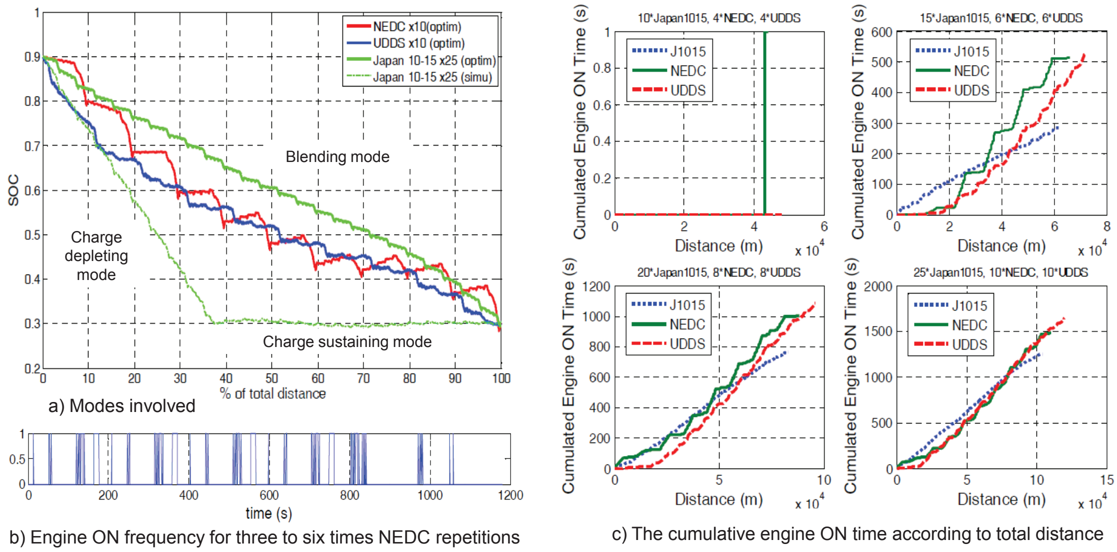


Figure 2.19: The control strategy; a) Modes involved, b) Engine ON frequency for three to six times NEDC repetitions, and c) The cumulative engine ON time according to total distance [91].

A. Konev and L. Lezhnev [92] implement a theory of probability and stochastic processes to reduce fuel consumption and emission of a series HEV. This is done by controlling the engine to work along or near the optimal operating points (OOP) line (Figure 2.20) to avoid aggressive engine transients. This will limit the engine power fluctuations, make it gradual and have a limited range. The controler employs the statistics learned on-line from the prior driving history, and uses low pass filter (PID controller) for optimisation. It is sub-optimal, gives reduction in calibration time and effort, improves robustness, has optimal engine operating line, ensures gradual operation (slowly varying), and can be use for on-line implementation.

A. Rousseau et al. [30] utilize divided rectangle (DIRECT) algorithm to search optimal solution by evaluating the objective function at the center point of the algorithm hypercube.

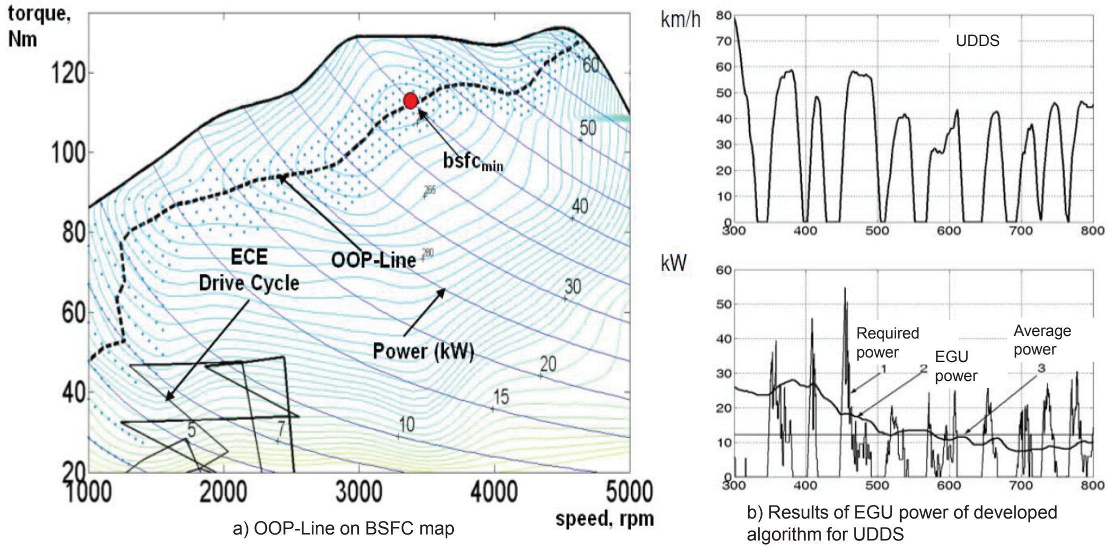


Figure 2.20: The concept of the control; a) OOP-Line on BSFC map, and b) Results of EGU power of developed algorithm for UDDS [92].

The algorithm divides the potentially optimal hyper-rectangles until termination of function evaluation or convergence of objective value. In this case, it is used to optimise six parameters of a parallel HEV system, which are the power thresholds and the moments: to turn the engine ON and OFF, and also the maximum and minimum threshold of the battery SOC (Figure 2.21 a)). It was tested with different values of parameters and distances of driving cycle and resulting in better fuel economy if the optimised parameters are yielded based on a longer distance but used for a short distance driving (Figure 2.21 b)). The best compromise is to use the parameters defined for the medium driving distance. This emphasizes that the method maximizes operating condition not only on charge depleting mode, but also on charge sustaining mode.

M. Amiria et al. [17] develop a control strategy that implement genetic algorithm as its evolutionary algorithm to reduce costs associated with loss of life cycle in batteries and manage their charge/discharge patterns to avoid deep discharging and frequent charging, since this will cause the battery's life to deteriorate dramatically. The thermostat on-off control method together with the optimisation algorithm are implemented in a series architecture to distribute the demanded power between the batteries and the E/G. This is multi-objective solution, which proves that with the proposed algorithm, the battery lifetime will be improved, and it can reduce fuel consumption and battery losses as demonstrated in Figure 2.22.

B. Zhang et al. [20] study the total optimization problem in a series HEV and apply evolutionary algorithm to the multi-objective optimization problem to have a good trade-off solution. It is designed to improve the vehicle fuel economy as well as to reduce its emissions such as

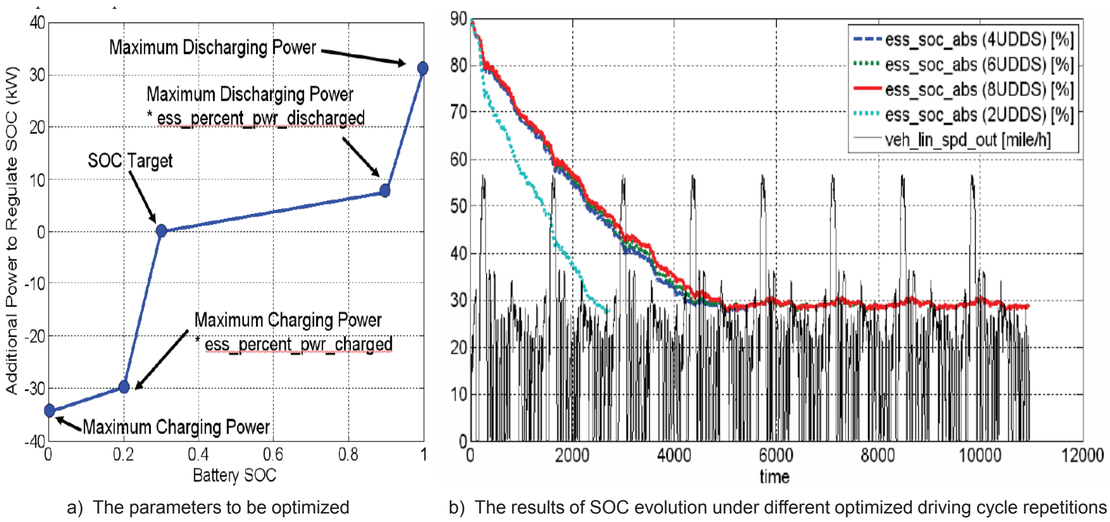
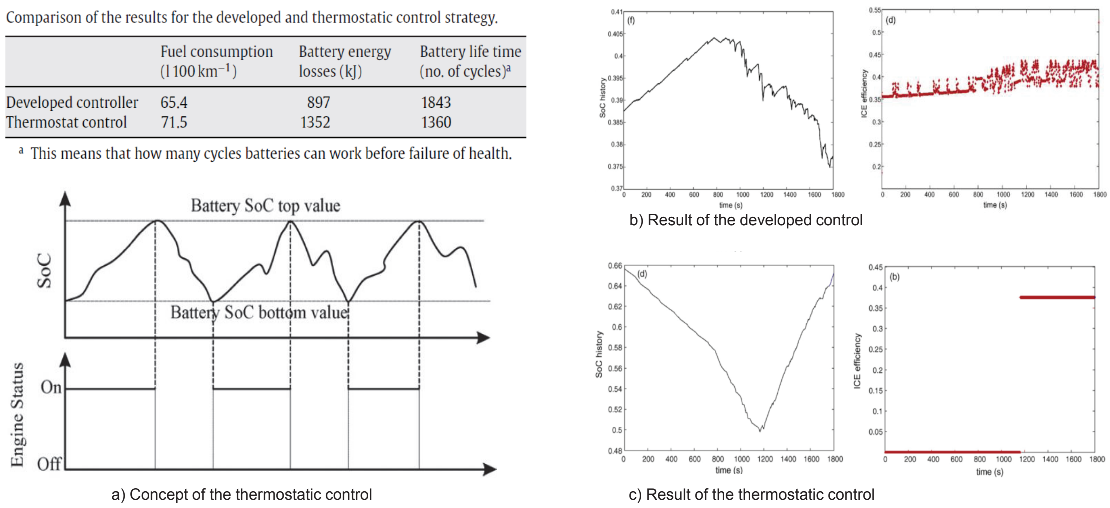


Figure 2.21: DIRECT algorithm; a) The parameters to be optimised, and b) The results of SOC evolution under different optimised driving cycle repetitions [30].


Comparison of the results for the developed and thermostatic control strategy.

	Fuel consumption ($l\,100\,km^{-1}$)	Battery energy losses (kJ)	Battery life time (no. of cycles)[a]
Developed controller	65.4	897	1843
Thermostat control	71.5	1352	1360

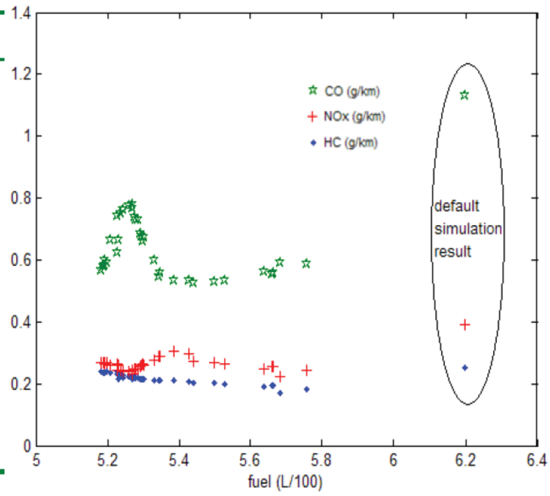
[a] This means that how many cycles batteries can work before failure of health.

Figure 2.22: Comparison of the developed control strategy and the thermostatic control strategy; a) Concept of the thermostatic control, b) Result of the developed control, and c) Result of the thermostatic control [17].

hydrocarbons (HC), carbon monoxide (CO) and nitrous oxide (NO_x) simultaneously. The Non-dominated Sorting Genetic Algorithm (NSGA-II) generates a population of multiple trade-off optimal solutions for thermostat on-off control strategy. The main task of a selection operator is to emphasize good solutions of population by making multiple copies of them to replace bad solutions of the population. The task of a crossover operator is to exchange partial information between two or more reproduced solutions and to create new offspring solutions. The task of a mutation operator is to locally perturb the offspring solutions. The controller design variables are as figured in Figure 2.23 (a). It compares the results of this method with a default ADVISOR controller and presents less consumption and emissions as in Figure 2.23 (b).

Design Variable	Description	Defaultvalue	Lower Bound	Upper Bound
eng_pwr	engine power	41kW	25kW	53kW
mc_pwr	motor power	75kW	38kW	112kW
ess_cap	capacity of batteries	26Ah	13Ah	39Ah
cs_high_soc	highest SOC allowed	0.8	0.7	0.85
cs_low_soc	lowest SOC allowed	0.6	0.3	0.5
cs_max_pwr	maximum power commanded of fuel converter	30kW	25kW	40kW
cs_low_pwr	minimum power commanded of fuel converter	20kW	5kW	20kW
cs_off_time	the shortest allowed duration of a FC-off period	Inf	10s	1000s

a) The controller design parameters to be optimized



b) The fuel consumption and emission of the trade-off solutions

Figure 2.23: Multi-objective evolutionary algorithm; a) The controller design parameters to be optimised, and b) The fuel comparison of emission of the trade-off solutions [20].

C. E. Nino-Baron et al. [25] propose a trajectory optimisation control strategy to satisfy energy demand in a predetermined time interval of a series hybrid vehicle. The performance function is to minimize the energy losses and allow the system to reach the final energy target as in equation (2.5). On a combined efficiency map, the subsystem (E/G) moves to a point of highest efficiency and stays until the energy requirement is satisfied (Figure 2.24). It explains three modes for the real time implementation: low energy requirement with enough time (common, at most efficient point, low losses), high energy requirement with enough time (higher power but low efficiency, operation is kept in this area to produce requested energy), and fast energy production (uncommon, at high torque and speed). The proposed method is proven to have better overall efficiencies than the classical control strategy while satisfying energy requirements.

$$J = h_1(W_{GEN} - W_{ref})^2 + h_2(W_{loss})^2 \tag{2.5}$$

S. Delprat et al. [93] apply optimal control theory as global optimisation solution for three different parallel HEV arrangements; the parallel single-shaft, parallel single-shaft with reductor, and parallel double-shaft. The control chooses an optimal pair of decisions at each sample time to minimise the total fuel consumption over a driving cycle. To avoid battery discharge during

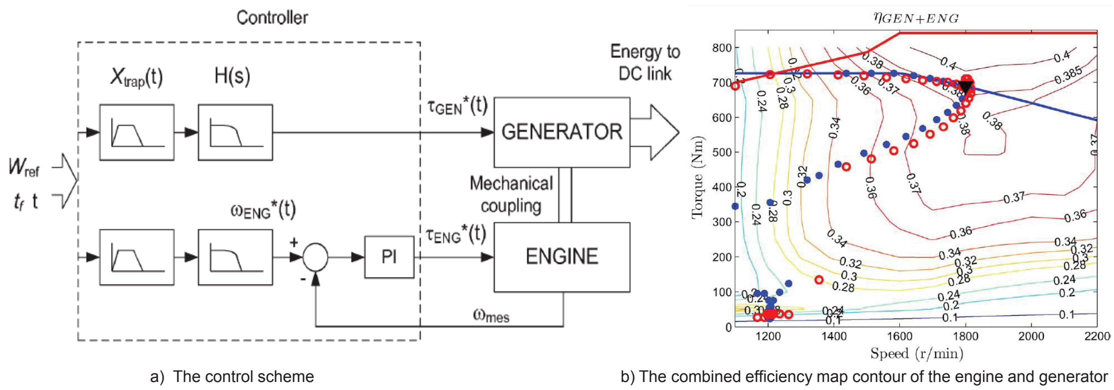


Figure 2.24: The trajectory optimisation control strategy; a) The control scheme, and b) The combined efficiency map contour of the engine and generator [25].

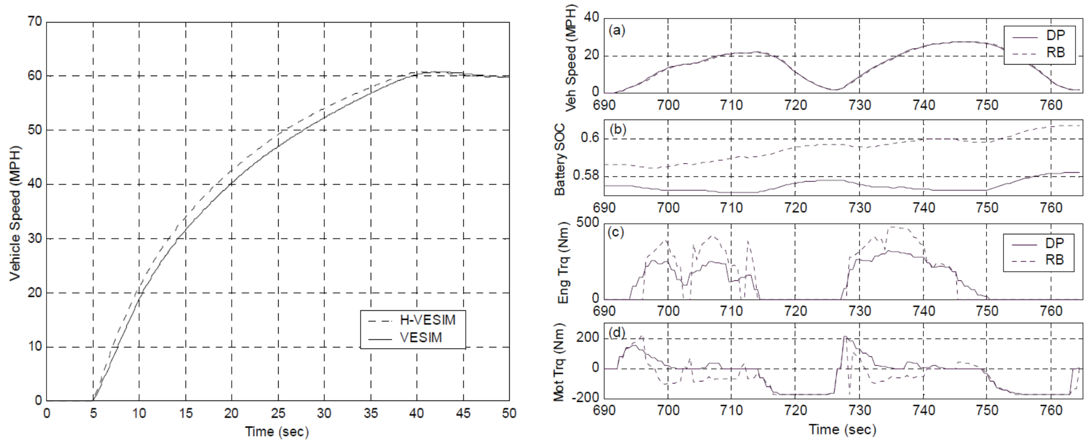
pure electric mode, it introduces a constraint of battery SOC and uses the classical Cardan's method to obtain the solution set.

In 2012, S. Kermani et al. [41] together with S. Delprat propose an approach based on Model Predictive Control (MPC) to predict the future driving conditions efficiently and for a sufficient long horizon. It implements minimum principle algorithm as its offline optimisation solution. The MPC considers a constant setpoint or a reference trajectory and is designed for rejecting disturbances. MPC has difficulties to be applied for HEV systems due to insufficient accuracy over a long horizon prediction, it is difficult to prove its stability, and a constant SOC control is not suitable for a short horizon. As solution, it proposes to comprise three controllers: the first controller, SOC corrector to control the battery SOC. The second controller, Prediction and Optimisation to compute the constant variable obtained with large sampling period. And the third controller, Powertrain control to control powertrain according to the constant at actual driving condition. The control is proven to be computationally efficient to be embedded in a real time predictive algorithm.

Dynamic Programming

A. Brahma et al. [37] utilise dynamic programming (DP) to formulate optimal power split for series HEV and optimise energy consumption. The optimal value function is taken as the least energy consumption from the current node to the end of the process. And the objective function is the overall energy consumed by the system in making a state transition. A tunable weighing parameter is introduced to penalize the amount of the stored or consumed electrical energy in each timestep which is equivalent to SOC deviation. If this parameter is 0 (no penalty), all energy is drawn from battery. Through this penalty function, it can impose the global integral charge sustaining constraint based on power flux in/out of the battery.

C. C. Lin et al. [8] introduce a rule based control method and use dynamic programming (DP) algorithm to compare the performance of the proposed control strategy. For the control strategy, the optimal combined charging-discharging efficiency is obtained around 60% SOC. The rule based algorithm has three modes (11 rules): normal mode (based on engine efficiency map and always operate in this region), charging mode (charge sustaining strategy to ensure SOC stay within lower/upper bound of 55-60%, engine will recharge the battery if SOC hits lower bound until reaching the upper bound), and braking mode (the regenerative braking is activated to absorb the braking power when the driver steps on the brake pedal). DP algorithm minimises a cost function to optimise fuel consumption over the complete driving cycle. Results show that the HEV system achieves earlier target speed of 0-60mph compared to a conventional truck (Figure 2.25 a)). The DP method produces higher fuel economy by exploring the efficiency of the whole system, has a smoother transition, but a lower SOC$_{final}$ (Figure 2.25 b)).



a) A conventional and a hybrid system acceleration

b) Results of the DP control and the RB control

Figure 2.25: Comparison of; a) A conventional and a hybrid system acceleration, and b) Results of the DP control and the RB control [8].

In 2003, C. C. Lin et al. [42] implement DP to minimise two cost functions for a fuel economy only case and a fuel/emission case over a driving cycle, because a preliminary rule based strategy improves fuel economy but increases NO_x level. It defines the battery charging and discharging efficiencies in function of power and SOC (Figure 2.26), then choose 55-60% SOC bounds to prevent battery depletion or damage. It defines the three control modes according to the power request (driver pedal): Braking Control (to capture as much regenerative energy, but the friction brake will assist if P_{req} exceeds the regenerative capacity), Power Split Control (as in Figure 2.27, ICE operates in high efficiency region, EM only if P_{req} is lower, ICE+EM if P_{req} is higher), and Recharging Control (ICE provides additional power to propel vehicle and recharge battery with a preselected power level, operation will become like a power split control if $P_{req} + P_{charge}$ is out of efficient region). The DP creates a family of optimal paths to reach desired $SOC_{terminal}$ of 0.57, shows a new optimal gear shift map (Figure 2.27) and achieves minimal weighted cost of fuel consumption and emissions. The tradeoff study provides information about the feedgas emissions sensitivity of NO_x and particulate matter (PM) due to fuel consumption. The results from DP is then used to improve a new robust rule based control strategy called Power Split Control (PSR).

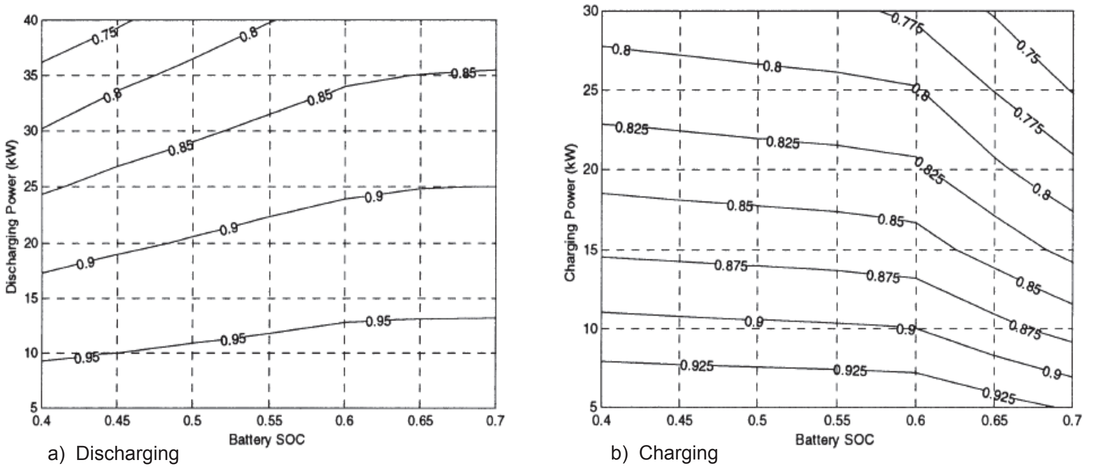


Figure 2.26: The efficiencies of the lead acid battery in function of power and SOC; a) Disharging, and b) Charging [42].

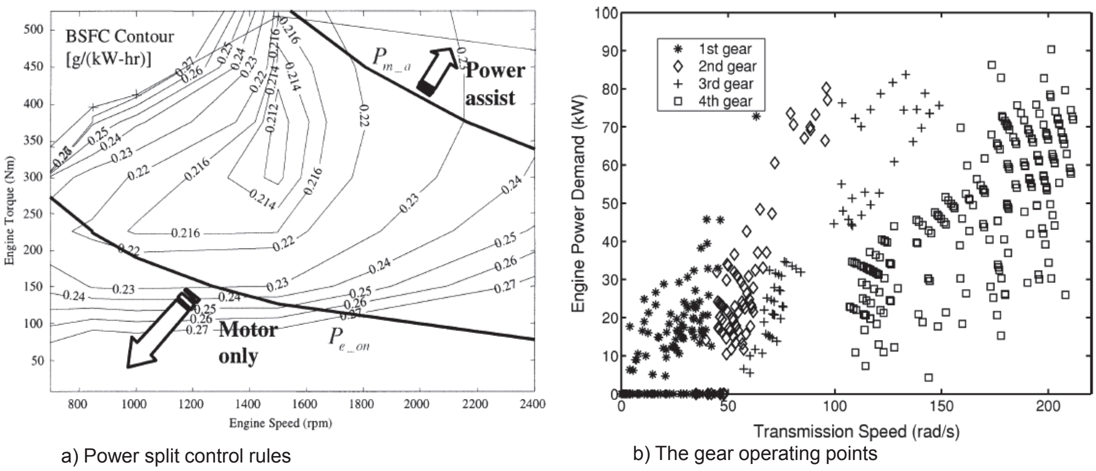


Figure 2.27: The DP optimisation; a) Power split control rules, and b) The gear operating points [42].

In 2004, C. C. Lin et al. [43] formulate an infinite horizon stochastic dynamic programming

(SDP) optimisation, modeled as Markov random process to improve fuel economy and reduce emissions. It interprets the driver throttle and brake pedal commands as power demand and input of the controller. It utilises the standard driving cycle to determine the transition probabilities. The sequence of observations is mapped into a sequence of quantized states by using nearest-neighbour quantization to estimate the probability distribution of future and synthetic power demands. The instantaneous cost is the weighted sum of the fuel consumption, NO_x and PM emissions, and a penalty for SOC deviation. Compared with a rule-based control strategy trained based on deterministic dynamic programming (DDP), the SDP achieves better performance over most of the test cycles. The solution is time-invariant state-dependent and has potentials to be fully integrated as optimal design and control process.

The works of J. F. Bonnans et al. [94] apply an optimal control to minimise fuel consumption along a dynamic trajectory. The optimisation problem is a bilevel optimisation. First, it computes the optimal control by discretizing the Hamiltonian-Jacobi-Bellman equations. Then, it optimises the design parameters by solving a nonconvex nonsmooth optimisation problem with a bundle method. To solve the high level problem, it uses bundle methods to collect relevant data along iterations in a bundle of information then, it generates the sequence of candidate points to define the model and stability points or prox-centers where objective functions decrease sufficiently. Candidate points are computed by solving a quadratic program. This is a convex quadratic programming problem which is easier to solve than linear programs. The computational burden is reduced by compressing the bundle information using aggregation technique which condenses it into one single data. Optimal control problem on the low level is solved by discretization of the battery level as a single state variable, fuel used as running cost, and penalization term as final cost.

M. Koot et al. [23] use DP to calculate the power setpoints for the alternator, and modify the algorithm to reduce computations because DP computation time is too large for a practical real-world application. It presents modifications such as using a simpler vehicle model, reducing the problem formulation to quadratic programming (QP), and posing requirements for vehicle information from the past and present. DP calculation can be done in acceptable time due to simple dynamics, but time can easily increase with the driving cycle length and the grid density. QP is used to decide the alternator setpoint, for the next time interval to achieve the smallest objective value over a certain trajectory, while satisfying the constraints. If QP is convex and by limiting the prediction length of the driving cycle, the global minimum can be achieved and computation time will be shorter. Model Predictive Control (MPC) is used to predict the driving cycle horizon. As results, the CO_2, CO, and NO_x emissions are reduced, but HC emission has increased. The fuel consumption and exhaust emissions are lower, owing recoverable energy from regenerative braking.

L. V. Perez et al. [95] implement DP to economize fuel consumption of a series hybrid vehicle on a driving cycle known a priori. It prefers to perform acceleration and deceleration using mainly the electrical path, since it is reversible. Energy is consumed if $P_{ESS} > 0$, but energy conversion is not perfectly efficient and have losses (2.6). Therefore, energy wasted during acceleration will be recovered during braking and the system use ICE to compensate the energy. At the same time, battery must not be depleted nor overcharged at any time to avoid irreversible damage. The battery has to work with a charge value in the interval $[Q_{min}, Q_{nom}]$, with $Q_{min} = 0.2Q_{nom}$. As a result, ESS is operated in a safe region during the whole cycle, the engine will have to provide part of the required power in the first stages. Then, it can be turned OFF and the ESS will perform the rest of the cycle by itself. As the initial charge of the ESS is sufficiently high, the solution indicates that the engine has only to be used when the demanded power is greater than the bound $P_{ESSmax} = 30kW$ (Figure 2.28).

$$f(P_{ESS}(t)) = \begin{cases} \eta_{ESS}(P_{ESS})P_{ESS} & if \quad P_{ESS} < 0 \\ \left(\frac{P_{ESS}}{\eta_{ESS}(P_{ESS})}\right) & if \quad P_{ESS} \geq 0 \end{cases} \tag{2.6}$$

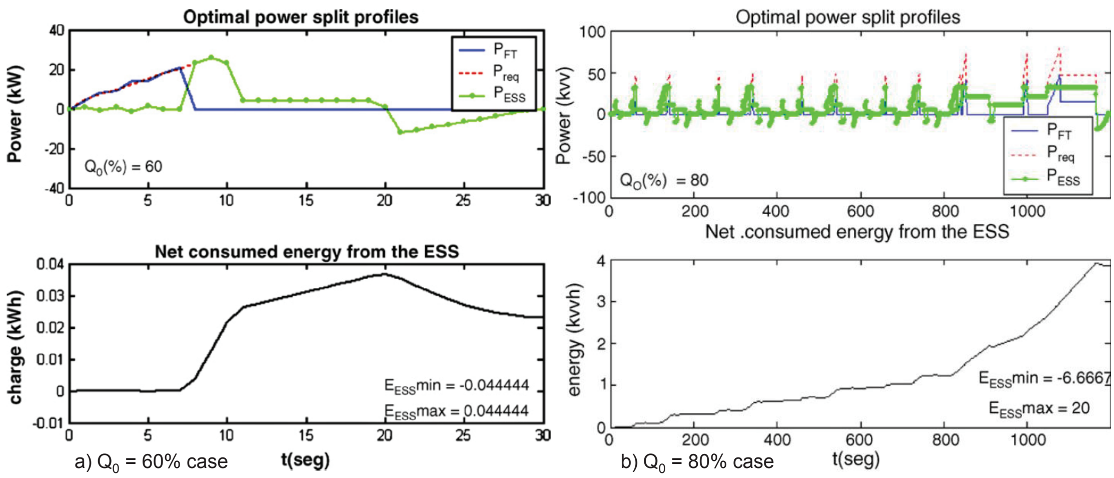


Figure 2.28: Results of power repartition of requested power (P_{req}), between P_{ESS} and P_{FT} of Q_{nom} = 0.92 Ah for; a) Q_0 = 60% case, and b) Q_0 = 80% case [95].

In 2007, Q. Gong et al. [96] propose a two-scale DP based optimal power management strategy with depletion mode for a plug-in HEV system. Firstly, the DP solves the macro-scale trip model for the whole trip based on historical traffic data to obtain the global optimal SOC profile, carried on off-line in advance by high capacity computational servers before transmitted to vehicle through wireless communication devices. Then, the micro-scale DP optimises the trip segments for a real-time optimisation by using vehicle on-board processors. The trip is divided to nearly equal segments (Figure 2.29) to acquire its real-time traffic flow when the vehicle gets close to a beginning of a segment. On-board wireless devices are used to obtain the real-time traffic data information needed for trip modeling. The SOC trajectories for the target SOC of the whole trip, short range DP, and the actual feedback is shown in Figure 2.29. The whole trip simulation using the average historic data of two weeks reveals a better consumption (3.81 L/100km) than using average data of a single day (5.37 L/100km). But, with the dual-scale DP, the consumption is 4.23 L/100km which is better than a conventional SUV and rule-based control. An analysis shows that after a segment size passing 20 points the fuel economy is constant, but the computation time will increase 4s/point.

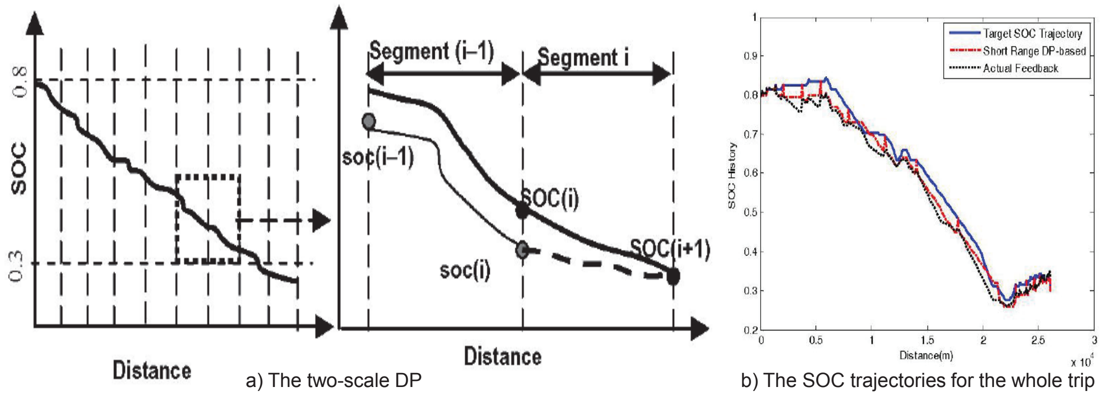


Figure 2.29: Comparison of; a) The two-scale DP, and b) The SOC trajectories for the whole trip [96].

In 2008, they continued their research [4] by implementing DP optimisation method to control the battery charge from its initial value of SOC highest healthy level of 0.8, to the lowest healthy level of 0.3. The system dynamics are considered as constraints. The gas kinetic traffic model is applied to model the driving cycle, leading to the trip model by deploying historical and real time traffic data for local road and freeway situations. The trip model uses detected speed values, interpolation, and a gas kinetic based traffic model considering on-or-off ramps. It is based on a kinetic equation for the phase-space density. A two scale DP then uses the trip model for optimisation that has show better computation efficiency and better fuel economy than a compared global optimisation solution.

Then, in 2009 Q. Gong et al. [78] develop a neural network (NN) based trip model for a highway portion using DP algorithm. The trip modeling considers two scenarios of local road and freeway. This article enhances the trip modeling by using path-finding algorithms inside the geographic information system (GIS) to search for the driving path and road information. This research considers the effect of the on-ramp or off-ramp on the freeway of one lane situation without lane changing. It proposes on field data-driven approach to record traffic data using Multi-layer Perceptron (MLP) of neural networks type. It acquires the on/off ramp traffic data for the target route from WisTransPortal agency to train the weights of neurons of back propagation based neural network. The neural network is used as function fitting tool with 3 inputs and 2 inputs. The pattern of traffic flow shows a slowed down traffic as it is approaching the on-ramp due to the mixing of inflow, then accelerate gradually after passing the mixing segment. The new approach of WisTransPortal with NN predicts the ramp flow on highway more close to the real test data. It compares the SOC profiles obtained between three DPs of the real test data, power splitting ratio (PSR), and PSR with NN. The DP PSR with NN (3.94 L/100km, 0.28) follows more closely the results of the DP from the real traffic data (3.72 L/100km, 0.28) in terms of fuel consumption and final SOC value than the DP PSR (4.49 L/100km, 0.37).

J. Liu and H. Ping [74] analyze two optimal controls, the stochastic dynamic programming (SDP) and the equivalent consumption minimization strategy (ECMS). The SDP objective is to find the optimal control policy π that defines the control decision of engine power demand, P_E based on SOC states, vehicle speed, and instantaneous power demand P_d. It uses power demand statistics of multiple driving cycles and extracts Markov chain driver model optimal control policy. The ECMS considers kinematic constraints imposed by electric machines and weights SOC to achieve SOC regulation. It searches among feasible values of the optimal engine power for each P_d, and then determines optimal engine power map for each vehicle speed offline. The results show that the engine operates very close to the theoretical optimum points and demonstrates continuous oscillation of the engine power commanded by ECMS as in Figure 2.30. The power profile provided by DP and SDP strategies are nearly the same and smoother, which is desirable from the drivability viewpoint.

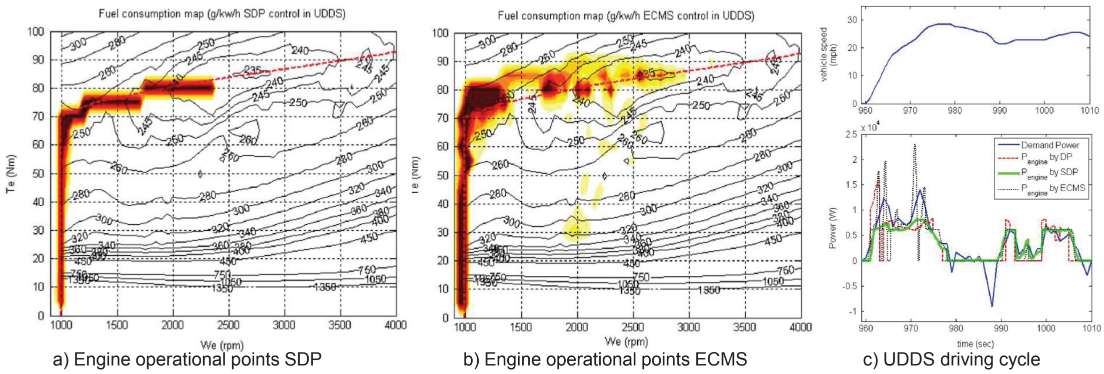


Figure 2.30: Results of the control strategies; a) Engine operational points SDP, b) Engine operational points ECMS, and c) UDDS driving cycle [74].

O. Sundstrom and L. Guzella [89] explain step by step a Matlab function that efficiently solves deterministic DP problems to achieve optimal control of non-linear, time-variant, constrained, discrete-time approximations of continuous-time dynamic models. This problem is solved using the Bellman's DP to minimise the cost function. It represents final cost and an additional penalty function to enforce a constraint on the final state. For the HEV system case study, it minimises total mass of fuel consumed during J1015 driving cycle. The constraints is to have $SOC_{initial}$

equal to SOC_{final} of 0.55.

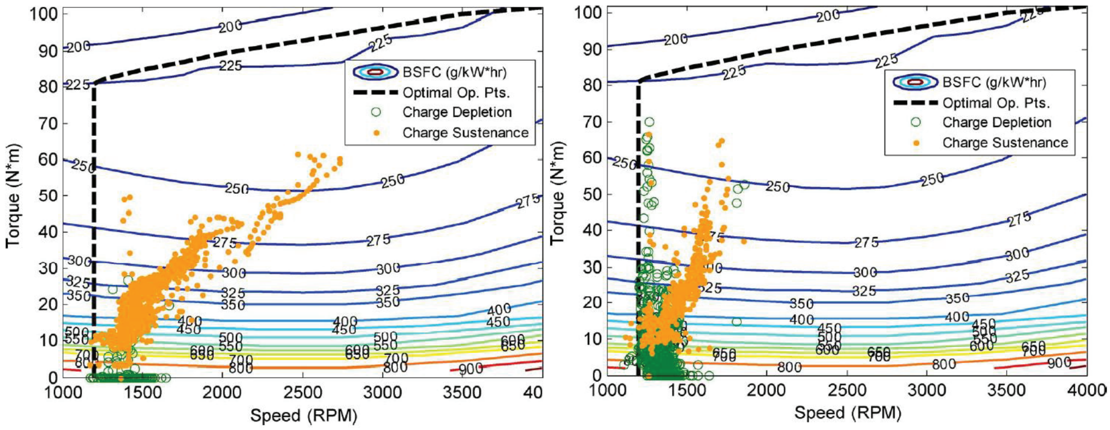
D. V. Ngo et al. [44] propose the path forecasting based control algorithm to optimize charging and discharging of the vehicle's battery whilst completing the preview route segment in a predefined time length. An utilisation of onboard navigation system allows Global Positioning System (GPS), Geographical Information System (GIS), and traffic information systems to help driver gains traffic information of a route segment such as road characteristics, traffic conditions, and speed limits. It uses Bellman's optimality principle, a time consuming computation due to its dimensionality criteria for the outer loop to find profile of optimal velocity. A gradient-based optimisation method is used for the inner loop to compute instantaneous optimal value of the control variable. The final optimal solution is expected to give the smallest value of cost function over a boundary of feasible traveled distance profiles.

D. F. Opila et al. [56] study drivability of a series parallel HEV system and use the shortest path stochastic dynamic programming (SP-SDP) in order to provide the approriate feedback and command signals along a given drive cycle using a causal driver model which are directly implementable in a real-time. The cost was a weighted sum of consumed fuel and drivability penalties based on shift events and engine on-off events. A baseline controller is compared to three SP-SDP and yield two possible design choices, an improved fuel economy with similar drivability or a similar fuel economy with reduced drivetrain activity. The SP-SDP controller allows more efficient ICE utilization and overall electrical propulsion, and also permits minimisation of friction braking.

S. J. Moura et al. [76] use stochastic dynamic programming (SDP) to optimise power distribution between energy sources and take into account the costs of those energies by controlling the charge depletion over aggressive depletion and its charge sustenance phase. The optimisation objective consists of two terms that define the costs of both energies with a coefficient to calculate trade-offs between those energies. The fuel consumption is then calculated to be converted to the battery's internal energy rate of change to replenish the battery charge consumed during the trip. To predict the future power demands, it uses a discrete time Markov chain-based drive cycle model as its stochastic component to compute optimised cost by selecting a finite number of sampled power demand and vehicle speed. It compares result of this fuel dominating cost charge depleting charge sustenance (CDCS) approach with those from baseline blended control strategy. The engine operation of both strategies is presented in Figure 2.31.

Real-Time Optimisation

A real-time optimisation can be implemented online because it has faster calculation time and can give a near optimal solution. It exists a generalization in determining the equivalence factor in ECMS. But this factor also has to be defined properly according to its operational modes or patterns of the past operation.

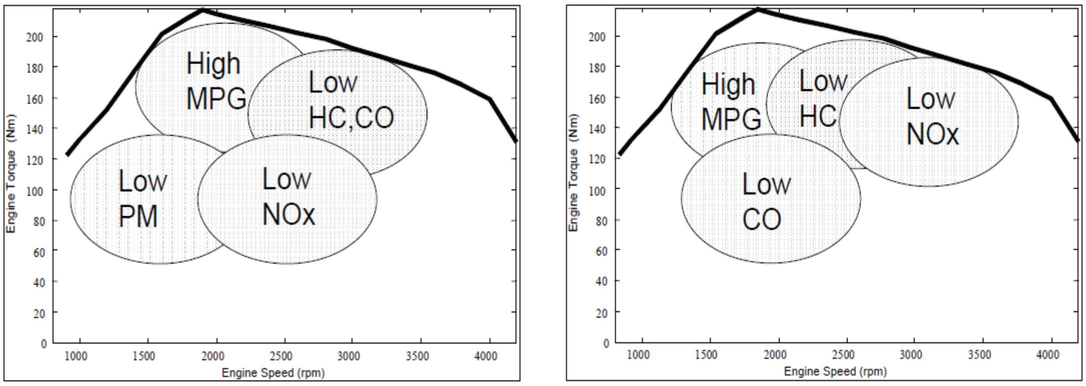


a) The CDCS approach engine operating points   b) The blended approach engine operating points

Figure 2.31: Comparison of; a) The CDCS approach engine operating points, and b) The blended approach engine operating points [76].

V. H. Johnson et al. [45] introduce a real time control strategy (RTCS) to optimise a parallel HEV efficiency and emissions. The strategy continuously selects the operating point that is the minimum of the cost function which is weighted by average fuel economy and emissions performance. The control strategy balances the trade-offs between the energy used and the four regulated emissions of HC, CO, NO_x, and particulate matter (PM). The representations of this emissions are as depicted in Figure 2.32. During regenerative braking, to capture a maximum amount of braking energy, the motor will handle all the negative torque by considering constraints imposed by the motor, the battery, the brakes, and vehicle stability. And if it is in torque assist mode, the sum of driver's power request is given by both torque from engine and motor. There are six steps to implement this controller. First, it must define the range of candidate operating points of acceptable motor torque for the current torque request. Secondly, it calculates the factors constituent for optimisation. Then, these factors are normalized for each candidate operating point. Next, the weighting is applied. In the fifth step, the performance target is applied. And finally, it calculates the overall impact function for all candidate operating points. The RTCS results in a significant drop of NO_x and PM emissions with comparable energy consumption.

P. Pisu et al. [97] present an energy management in a hybrid vehicle to assure an optimal use and regeneration of the total energy to maintain charge in the energy storage system (ESS). The objective is to operate the powertrain with maximum fuel economy over a given trip. It assigns the future fuel savings and costs to the actual use of electric energy to sustain battery charge. It presents the cost in terms of fuel and the average efficiency during discharging mode and recharging mode of the ESS. Then, it explains a control for drivability to assure acceptable drivability of a vehicle like smooth gear shifting and minimum excessive driveline vibrations.



a) CIDI engine b) SI engine

Figure 2.32: Fuel economy and emissions tradeoffs for; a) CIDI engine, and b) SI engine [45].

J. Park et al. [10] develop a real time controller of a series parallel HEV to optimise choice of engine intantaneous operating point. The system is equipped with an electrical continuous variable transmission (E-CVT), which combines a planetary gear set and two electric machines. The optimisation is divided into two stages, the determination of a target charge/discharge power and the determination of ICE operating point. The average discharging efficiency is derived from the total electrical energy loss and is used to estimate the future potential charging power. The operating point of the ICE was determined based on the system efficiency map and SOC is maintained the same over the driving cycle. Simulation shows that the ICE operates in an efficient area, but it deviates a little from the optimal operation line (OOL). The controller performance is validated through hardware in the loop simulation (HILS) and is executable in a reasonable time limit.

G. Ripaccioli et al. [75] develop a stochastic model predictive control (SMPC) to optimise the power split among its power sources i.e fuel power and battery power, while fulfilling bounds on the battery SOC and the power availability. Markov chain model represents the driver power request to optimise the distribution of future power demand at each sample time, given the current one. The system stochastic description is constantly updated online which relates more to a particular driver and daily use of vehicle. The model is used to generate an estimated power request, which is assumed to take a finite number of values. It is defined by a transition propability matrix, t_{ij} that characterizes specific driving-cycle estimated from known cycles of past driving records and standard driving cycles. The SMPC approach uses the updated information on the system state and on the Markov chain to build an optimisation tree consisting nodes at every time step. The resulting control law allows only one control move for every node. They compare the SMPC with the frozen-time MPC, and the precient MPC (PMPC). The PMPC has the smoothest power trajectory and the best fuel consumption is used as benchmark.

As a result, the SPMC improves the fuel consumption by 13.5%.

S. Stockar et al. in 2010 [46] propose an optimal control theory solved by Pontryagin's minimum principle (PMP) to produce an on-line solution. It takes into account the on-board electricity consumption during vehicle operations and allows charge depleting operation. It associates CO_2 mass produced by the engine, $m_{CO_{2,f}}=\kappa_f.P_f(t)$ and consumption of the electric energy on-board, $m_{CO_{2,e}}=\kappa_e.(P_{batt}(t)/\eta_{ch})$. It assumes κ_f=0.294 kg/kWh for the Diesel engine, κ_e=0.567 kg/kWh for the USA electricity production scenario, and η_{ch}=0.86 for the battery grid charging efficiency. The PMP converts a global optimal control problem into a local minimization problem, thus requiring less computation and allowing it to be solved continuously. The optimal control policy is minimised by Hamiltonian function at each time, t and is limited by some conditions. One of this limitations is the Lagrange multiplier, μ to penalize battery utilisation if state of energy (SOE) is at lower bound and to facilitate the use if the battery is fully charged. The parameter λ_0 and μ were chosen iteratively referring to a driving profile considered in this study. The derivative of the battery efficiency, $\lambda(t)$ is a function of the SOC. The initial SOE is set at 0.9. Through simulation, a negative value of λ_0 resulting a charge sustaining operation. If the value is greater than 10, the SOE depletes until the lower limit, then switches automatically to charge sustaining mode. With λ_0=6, the charge is slowly depleted and reaches its lower bound at the end of driving path, thereby resulting the best fuel economy.

Then in 2011, S. Stockar et al. [47] propose a supervisory energy management to deplete battery charge of HEV system by considering the vehicle energy consumption from fuel and electric grid. The cost function is to minimise the vehicle cumulative CO_2 emissions and not the fuel consumption over a mission because in plug-in HEV the energy of battery is supplied by the grid. And the mass of CO_2 produced relates the vehicle variables of specific CO_2 content in the fuel and electricity per kilowatthour. The control and state variables are subject to constraints to prevent abuse and battery aging related issues. The method adapts the extended Hamiltonian function to simplified the problem on defining inequal constraints. The strategy is then implemented on a plug-in HEV simulator to evaluate its sensitivity through different vehicle utilization and energy generation. It is proven to be low sensitive to the driving profile characteristics such as energy demand or driving distance. But, it is very sensitive toward the vehicle operating mode and a control parameter, λ_i that affects SOE profile. A higher sensitivity is observed for energy generation characterized by a low CO_2 content. This method is useful to understand formalization of vehicle trajectory as guide to design a real-time energy management.

J. Cao et al. [33] design an EV system of a battery as a main source and an ultracapacitor as an auxiliary source to increase driving range. Ultracapacitors that has a high specific power are utilized as an auxiliary source to receive fast regeneration power and provide peak power, because batteries have poor ability to recover energy from regenerative braking and a scarce power capacity for a fast acceleration. To manage the power flow between both sources, an optimal control strategy of μ synthesis robust controller is developed to improve the energy-regenerative efficiency. The operation of the system is as follows: during start-up process, both energy sources drive the motor together. At normal speed, the batteries drive the motor alone while recharging ultracapacitor as preparation for acceleration or climbing situation. The EV driving control has uncertainty, Figure 2.33 shows the connections and relations of its nominal model G_0, the feedback structure K_d, the uncertainty model (z, p, u, y, d, e), and the performance index. To enable the closed-loop system to be still and maintain stable in pertubated situation, a stable controller K_d is to be found by selecting weighting functions of performance index, model uncertainty, and input that gives the structure singular value, μ to be less than 1. Thereafter, the control problem has to be transformed from an equivalent open-loop control system, to an equivalent closed-loop control system after adding K_d, and finally to a closed-loop linear fractional control system. As a result, μ is found to be 0.768. The system is proven to have strong robust stability, good capacity of command signal tracking, anti-interference, and noise-suppression to resist disturbance. The robust controller is proven to be efficient in recovering more energy and lengthening batteries life. It also can enhance EV instanteneous performance, avoid batteries being charged and discharged by big electric current, and reduce batteries charging times.

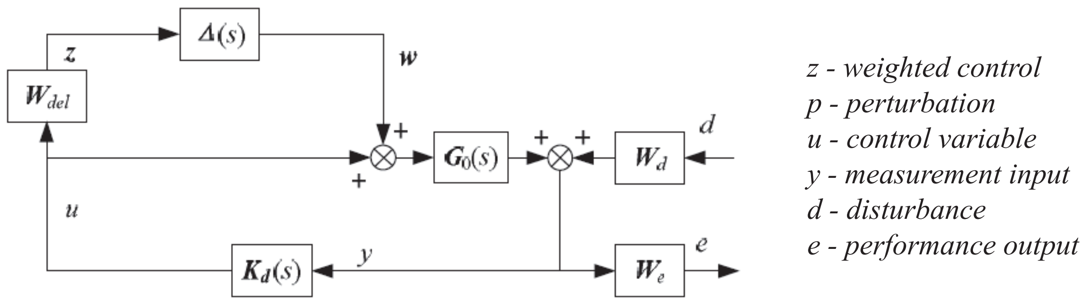


Figure 2.33: The EV driving control system with the uncertainty [33].

Equivalent Consumption Minimisation Strategy (ECMS)

A. Sciaretta et al. [48] evaluate the equivalence factor between fuel and electrical energy based on system self-sustainability, and is valid for different system architectures. The cost function $J(t, u)$ is minimised to find the value of control variable $u(t)$. The equivalence factor $s(t)$ varies with time, weighted the electricity energy used. If $s(t)$ is too large then $m_{fuel}(t)$ increases, if $s(t)$ is small then electrical energy will be used. First, it introduces s_{dis} and s_{chg} to evaluate the equivalent fuel at the end of driving cycle, then it introduces a probability factor $p(t)$ to choose s_{dis} or s_{chg} during cycle, and finally evaluates $p(t)$ during real time. The ICE works on a steady operating point. It prevents frequent engine starts/stops by evaluating an equivalence factor $J_{ss}(u, t)$ that consider additional fuel energy related to this problem. It utilises s_{dis} to weight the required electrical energy use. This ECMS objectives help to minimize fuel consumption, minimize SOC deviation, and avoid frequent startups. It introduces λ as a constant ratio of free energy $\bar{E}_{e0}/E_m$ over time. The ECMS result in term of fuel consumption and battery charge sustainability are very close to those of global optimal solution. And, it is capable to reduce the number of startups as shown in Figure 2.34.

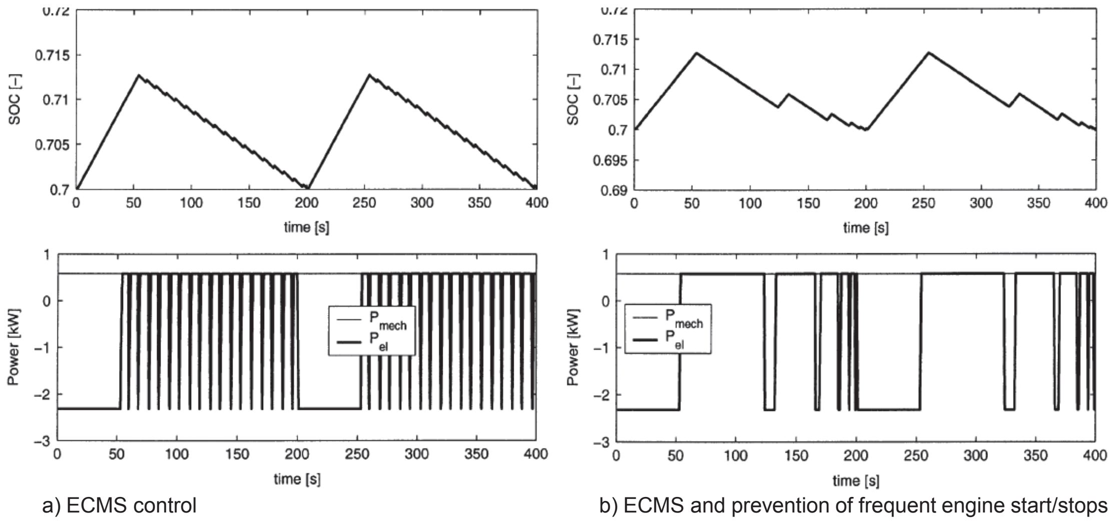


Figure 2.34: SOC evolution and number of startups before and after ΔJ_{ss} modification results; a) ECMS control, and b) ECMS and prevention of frequent engine start/stops [48].

C. Musardo et al. [70] propose an adaptive-ECMS (A-ECMS) to sustain battery SOC and improve fuel economy over the vehicle trip. It estimates the equivalence factor according to the current driving conditions. The control is instantaneous, subjected to integral constraints like maintaining SOC, meeting driver demand, and respecting the components limitations. It assumes that every variation in SOC will be compensated in the future. Firstly, the equivalent fuel rate due to the battery energy use is represented with a pair of equivalence factors during discharge, s_{dis} and recharge, s_{chg}. The approach can provide optimal solution if the pair is tuned perfectly according to driving cycle, known a priori. This means the pair should be properly tuned every time the nature of the cycle changes. Thus, it builds an adaptive algorithm that updates the control parameters for the current mission by combining past and predicted vehicle speed, and data from GPS, and it determines an unique equivalence factor s, which is the average of the pair to reduce computation problem. The fuel consumption is close to those from DP optimisation for the standard driving schedules. SOC_{final} is the same as $SOC_{initial}$, but when there are significant changes in the cycle, the SOC deviates from the reference value of 0.7.

D. Ambuhl and L. Guzella [68] utilize the available information on the future driving profile to compute a reference trajectory for the SOC to avoid regenerative energy to be wasted in the conventional brakes (Figure 2.35). It identifies the changes in SOC reference trajectory as to respect the upper and lower bound of SOC. During free segments, the supervisory control can control the SOC by penalizing or favorising the use of electric path, but during fixed segments, the use of the electric path is determined by the driver or cycle where it can happen that SOC violates its constraints whenever the powertrain is in boost mode or recuperation mode. The controller identifies the future fixed segments from data of the navigation system, estimates the recuperable energy and converted into the future SOC changes. It combines the nonpredictive ECMS to lower the SOC before an important recuperation phase with its predictive reference signal generator (pRSG-ECMS) to ensure recuperation of available energy and minimize consumption. Comparison of results are made between DP, ECMS, and this control strategy. The control strategy is proven to be effective in maximizing the amount of recuperated energy while respecting constraints of battery SOC.

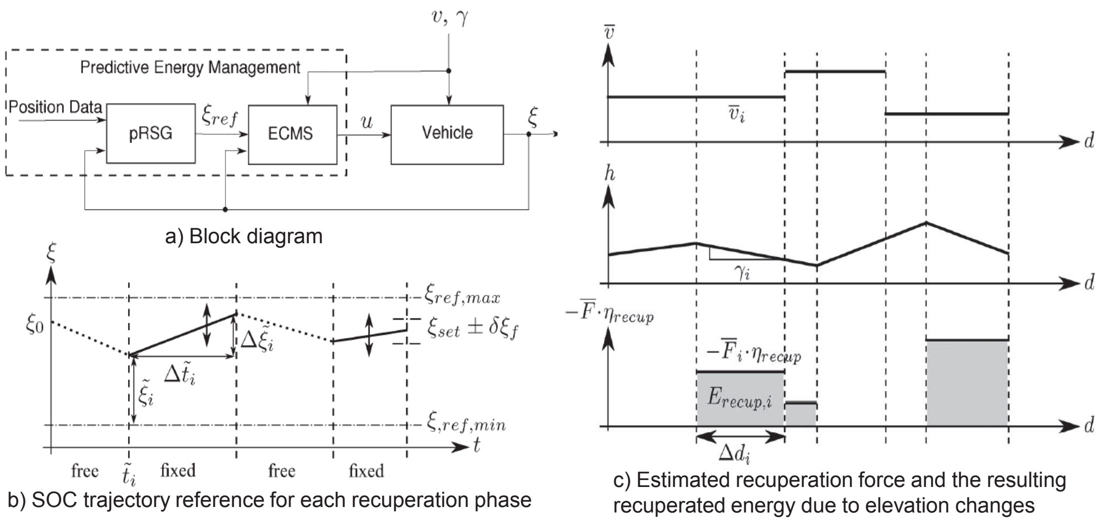


Figure 2.35: The concept of the pRSG-ECMS control strategy; a) Block diagram, b) SOC trajectory reference for each recuperation phase, and c) Estimated recuperation force and the resulting recuperated energy due to elevation changes [68].

J. Gao et al. in 2007 [49] compare between three control strategies for a series HEV namely the thermostat on-off (TCS), the power follower (PFCS), and the equivalent fuel consumption (EFCOCS). The controllers determine the power given by engine/generator set, P_g based on the power requirement, P_r and SOC. The battery electric power, P_b is the remaining power needed by the vehicle, $P_b = P_r - P_g$. The objectives of the control strategies are to determine the power distribution between the prime mover (PM) and the ESS so that the power requirement and other constraints are satisfied, and to minimize fuel consumption and harmful emissions. The TCS turns ON and OFF the engine based upon SOC and operates the engine at its highest efficiency point. The PFCS activates the engine/generator set all the time except during low power request and SOC higher than SOC_u. It prevents on-off frequency of ICE. The EFCOCS defines the constants of battery operation during charge, C_{chg} and discharge, C_{dis} to recharge the battery with an equivalent fuel consumption. It limites the power output rate and the off-time of ICE. As a result, EFCOCS has better fuel consumption than PFCS and TCS, with higher SOC_{final}, thus this article choses the EFCOCS that gives the best overall efficiency, eventhough TCS can provide the best efficiency of engine/generator set, while PFCS can sustain SOC with a stable bus voltage.

Then, in 2009, J. Gao et al. [14] state that charging and discharging the battery with high current shall be avoided due to low charge and discharge efficiency which will reduce battery life. It proposes an equivalent fuel consumption optimal control strategy (EFCOCS) to determine the power distribution between the primary energy converter and the renewable electrical storage system. It proposes the equivalent fuel consumption to be used is determined by the fuel economy coefficients C_{ch} and C_{dis} during charging and discharging operations respectively. The performance of this control strategy is compared with the thermostat control strategy (TCS) and the power follower control strategy (PFCS). The TCS provides the best efficiency for the engine/generator set, leading to good fuel economy performance under highway driving conditions. The PFCS provides sustainable SOC regulation with a stable bus voltage, improves the battery durability and that of other electrical components with good fuel economy performance during urban driving. The EFCOCS provides a reasonable power distribution between the engine/generator set and battery pack (Figure 2.36), leading to the best overall fuel economy under both urban and highway driving conditions, and outcomes fuel economy close to the global optimization data.

B. Geng et al. [73] study a power management for a micro-turbine (MT) of a plug-in hybrid called T-ECMS that uses telemetry information and aims to minimise the vehicle driving cost as in equation (2.7). T_s is the sampling time, the subscript K is a time index, N is the number of sampling steps in the driving cycle, η_e is the electric grid charging efficiency, ξ_1, ξ_2 are the market price of diesel and grid electricity, respectively. If P_{elec} is positive, it will charge an equivalent electricity, and contrary will save an equivalent energy cost if P_{elec} is negative. The control strategy permits the battery SOC to vary only within its limit range, $SOC_{low} \leq SOC \leq SOC_{up}$. The solution is subjected to dynamic, state variable, and input constraints. The authors propose a predictive on/off control to deplete from initial SOC of 0.8 to SOC_{low} of 0.4 at the end fo a driving cycle. It detects the vehicle location to the destination with an onboard GPS. It assumes that the driving manner and traffic conditions remain unchanged. The distance the vehicle can travel in one charge/discharge cycle is denoted as L. If the distance left of the cycle, $L' \leq 0.95L$ the MT will be switched on. The MT switch on time, $t_{on} = \delta_{corr}(E_{avg}L')/(P_{MT}\eta_{conv})$ is the period to charge the battery at its peak power, with δ_{corr} is the average electrical path efficiency. Analysis on DC bus energy requirement against travelling distance shows an average energy utilisation around 700 kJ/mile for the NEDCs, UDDSs, and WVUINTERs driving cycles. The

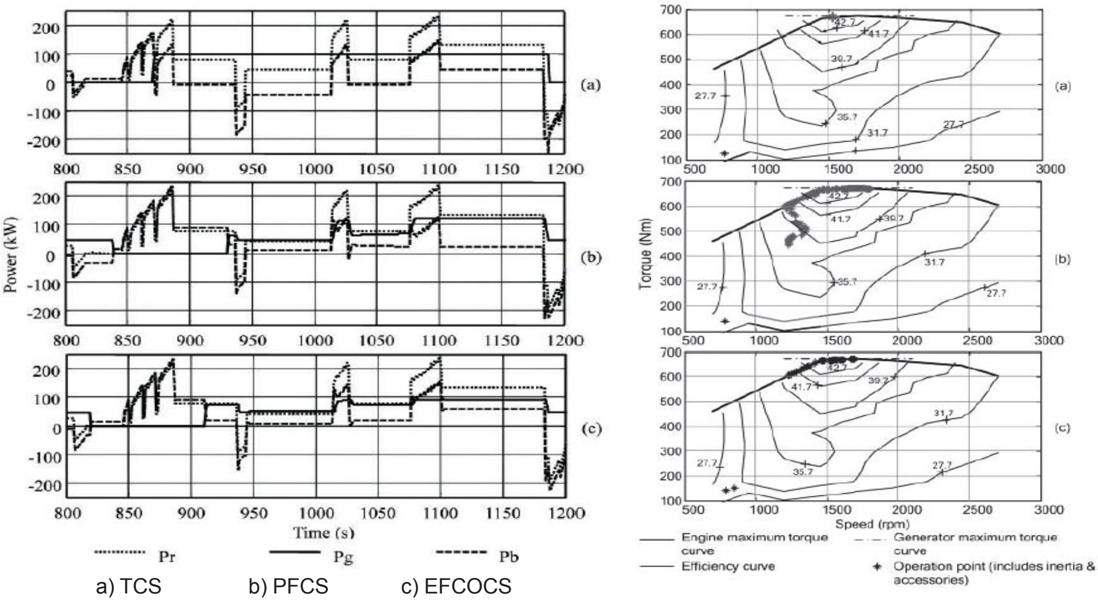
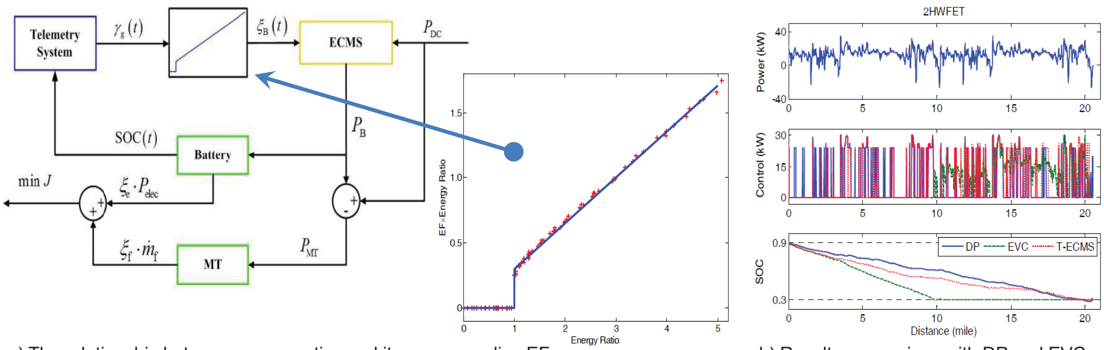


Figure 2.36: The power distribution and the engine operating points comparison of the three control strategies; a) TCS, b) PFCS, and c) EFCOCS [14].

fuel consumption and driving cost of this predictive on/off is close to that of DP, and better than those of traditional ON/OFF control.

$$COST = \xi_1 T_s \sum_{K=0}^{N-1} \dot{m}_{f,K}(P_{MT,K}) + \frac{\xi_2 T_s}{\eta_e} \sum_{K=0}^{N-1} P_{elec,K} \tag{2.7}$$

B. Geng et al. [9] use ECMS with Pontryagin minimum principle (PMP) to minimize driving cost. The optimal controller T-ECMS defines the vehicle energy gap at time t represented by the future energy use over the remaining part of the trip and the recovering energy saved after a certain time during a cycle. The energy gap $\hat{E}_g(r) = L(1-r)K(r)$ is approximated in real time, with vehicle position $r = l(t)/L$ where $l(t)$ is a distance already travelled by the vehicle. $K(r)$ represents the energy gap reduction rate per unit driving distance. The energy ratio is introduced to predict the equivalent factor (EF) in real time and regulate large battery SOC trajectory problem. As shown in Figure 2.37, if the ratio is less than one, the system functions as EV during the entire trip. If the energy gap is larger than onboard battery energy (energy ratio is greater than one), EF increases to penalize battery energy usage. The energy ratio and EF relationship does not change regardless of different driving cycle for a constant fuel price. Comparison is made between this control strategy, DP, and electric vehicle control (EVC). As a result, EF is adaptively changed with SOC feedback information, hence robust to control parameter inaccuracy in T-ECMS. T-ECMS exhibits similar performance to DP in driving cost and diesel consumption over both urban and highway cycles. The approach is insensitive to the selection of control parameters, K and κ, but as the driving distance increases, the driving cost grows higher because the battery could not meet the total energy demand of the vehicle.

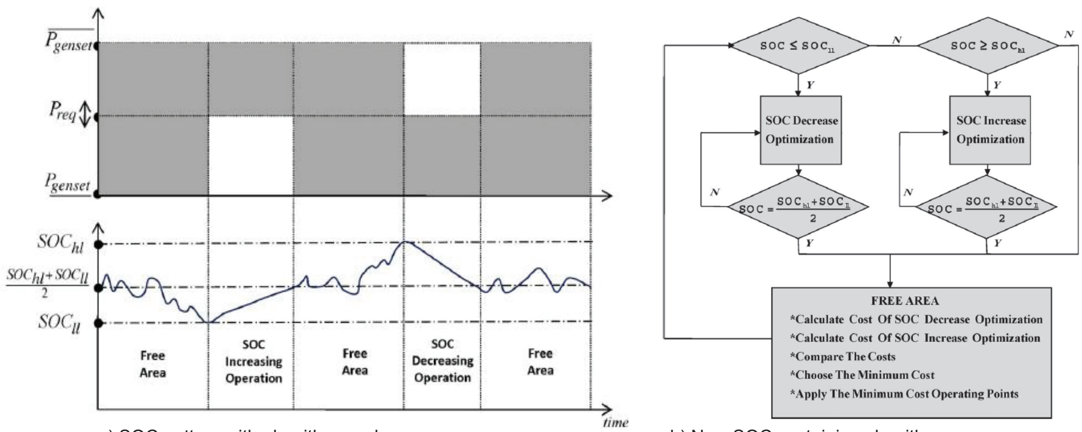


a) The relationship between energy ratios and its corresponding EFs b) Results comparison with DP and EVC

Figure 2.37: Schematic illustration of T-ECMS; a) The relationship between energy ratios and its corresponding EFs, and b) Results comparison with DP and EVC [9].

V. Sezer et al. [26] design a novel ECMS for a series HEV to improve optimisation performance by proposing a new approach to sustain battery charge. The approach changes the function of SOC deviation with real SOC value as an optimisation constraint and not as penalty function to avoid SOC draining or overcharging. It determines SOC upper and lower limit (selected 0.704 and 0.696 respectively) not to start or stop the genset, but as a region to optimise the genset delivered power. Once the rated SOC is reached, the algorithm is relaxed for the search to yield a more flexible and efficient performance. This method uses a combined cost map for pollutant emissions to reduce computational burden. The formulation of these maps are as in equation (2.8) depending on weighted value, k_i. Different maps can be built and used according to control goal. It provides optimised control strategy for the genset power [10:0.5:104] kW. Then the ECMS produces the reference genset power according to power demand. It is imposed that the battery usage will be regained in the future operation considering battery efficiencies in its cost calculation. It introduces three genset operation modes, the SOC increasing, the SOC decreasing mode, and the free operation mode. The operation of this new SOC sustaining algorithm is shown in Figure 2.38. Comparisons are made with an on-off control strategy, a classic ECMS and a conventional mode. The results demonstrate a significant reduction in CO_2 emissions and fuel consumption, and a smaller reduction ratio for NO_x and HC emissions compared to other control strategies. The ICE operating points and SOC variations are compared in Figure 2.39.

$$C_f(\omega, T) = \frac{k_1 C_{CO} + k_2 C_{CO_2} + k_3 C_{FC} + k_4 C_{NO_x} + k_5 C_{THC}}{k_1 + k_2 + k_3 + k_4 + k_5} \tag{2.8}$$



a) SOC pattern with algorithm modes b) New SOC sustaining algorithm

Figure 2.38: Schematic illustration of the new SOC sustaining ECMS algorithm; a) SOC pattern with algorithm modes, and b) New SOC sustaining algorithm [26].

L. Serrao et al. [7] make a formalization of three ways of optimisation solution for HEV. It decribes and analyzes dynamic programming (DP), Pontryagin's minimum principle (PMP), and equivalent consumption minimization strategy (ECMS). In a HEV system, the optimal control finds the sequence of controls $u(t)$ that leads to the minimization of the performance index J. The optimisation is subjected to constraints like system dynamics, initial state value, terminal state value, instantaneous state limitations, and instantaneous control limitations. It applies these control methods on a series HEV, and the genset is operated along its maximum efficiency line or optimal operating line (OOL). DP is based on Bellman's principle of optimality, writen in discrete form, and defines the cost-to-go as the cost incurred in moving from a time step to an end of horizon. DP needs a backward procedure, the solution can only be found offline for a driving cycle known a priori, and it has high computational load, thus it is not implementable online. The PMP can be used to find candidates of solution by minimization of Hamiltonian function at each instant, the solution is optimal if the function is a convex function of the control. It has to define two-point boundary values of initial SOC using iterative procedure and final value of the SOC that is defined at the final time. It can obtain convergence in few iterations, faster than DP by using a bisection procedure. The ECMS solves the optimisation problem without information about the future at each instant. The equivalence factor s is used to convert electrical power into equivalent fuel consumption to sustain battery SOC. If the SOC is above SOC_{ref} the battery will likely be discharged, and it will penalize fuel use if SOC is lower than SOC_{ref}. It is represented as correction term $p(x)$ as in Figure 2.40. Normally, the equivalence factor is constant, but in particular cases it can be characterized by battery charge and discharge operation or vehicle operating modes. The choice of s can affect SOC behaviour to charge depleting, charge sustaining, or charge increasing trend. Therefore, for a trend chosen, s tuning is necessary for

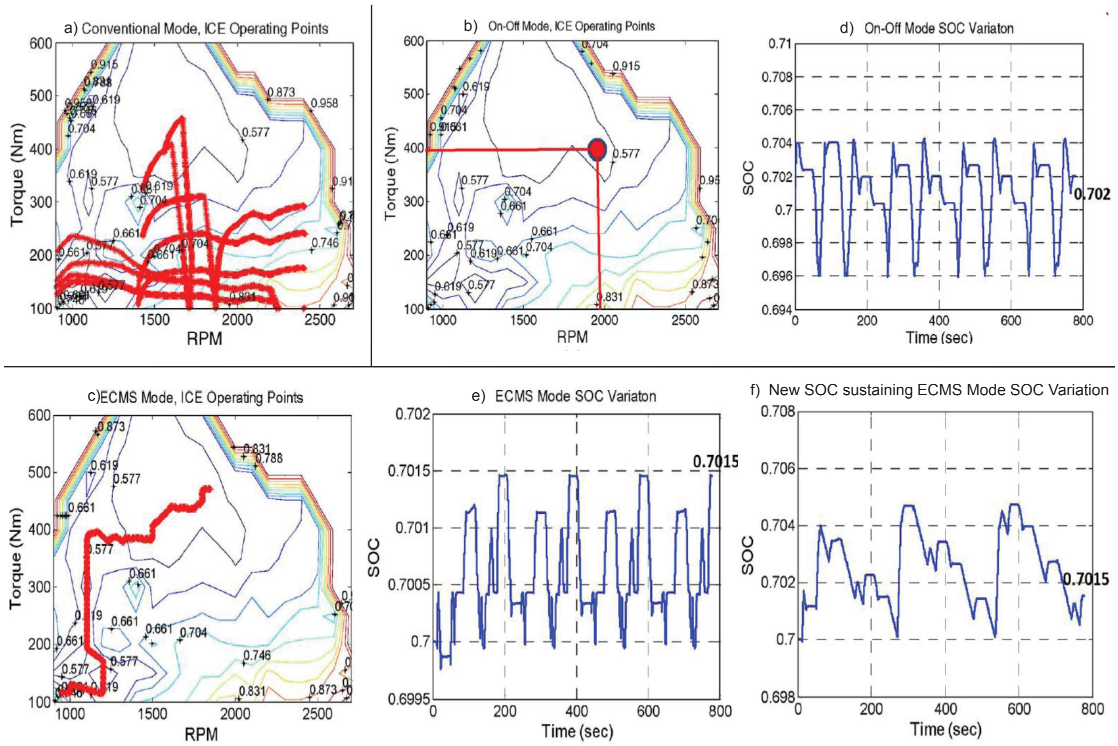
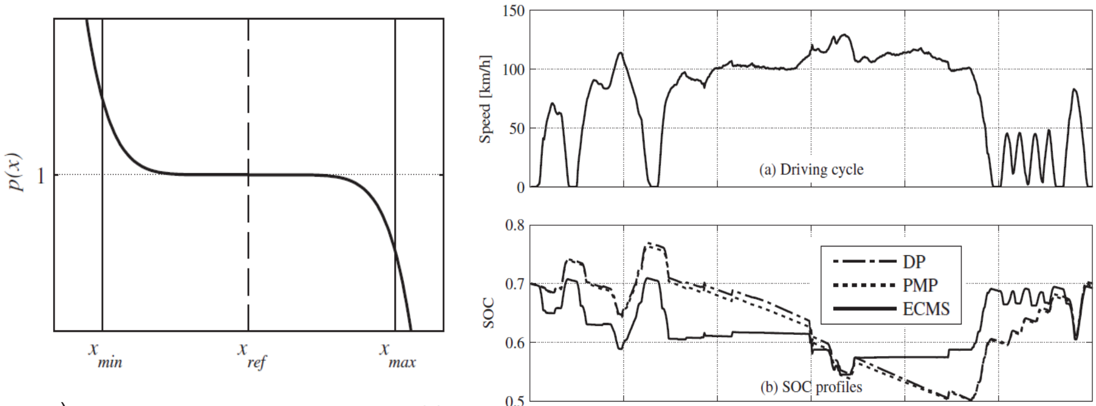


Figure 2.39: Comparison of ICE operating points on a combined map of k_1=0, k_2=0.5, k_3=0.5, k_4=0, and k_5=0 for; a) Conventional mode, b) On-Off mode, c) ECMS mode, and comparison of SOC variation between; d) On-Off control strategy, e) Classic ECMS mode, and f) New SOC sustaining ECMS mode [26].

each type of driving cycle to minimize total fuel consumption. As results, the DP and PMP provide the same solution which first increases the SOC, then decrease steadily during high-power phase, and finally increases to reach desired terminal value (Figure 2.40). The ECMS tends to react similar to the power demand trends and it needs more fundamental understanding of the equivalence factor to be adapted for all driving cycle.

C. Zhang and A. Vahidi [28] deploy instantaneous real-time minimization strategy of equivalent consumption minimisation strategy (ECMS) to enhance energy utilisation of plug-in HEV by using terrain, traffic, and trip distance preview. This method relies on instantaneous power demand, vehicle velocity, and battery SOC to reduce fuel use and sustain battery charge. In a PHEV, the batteries can be depleted to their minimum allowable charge by the end of a trip to achieve maximum energy efficiency. The combustion engine and electric motor utilisation are blend throughout the trip to have an optimal solution, so that the battery is nearly depleted when arrive at charging destination. This work optimises the decision to operate the PHEV in blend charge-depleting (CD) mode or all-electric CD mode by using information of future driving



a) **SOC correction term for ECMS, *p*(*x*)** b) Comparison of the three strategies on US06 cycle

Figure 2.40: New ECMS control; a) SOC correction term for ECMS, $p(x)$, and b) Comparison of the three strategies on US06 cycle [7].

conditions. It integrates long-horizon preview information by classifying four level knowledge of future events: 1) full knowledge of distance, upcoming terrain profile and future velocity (use DP and ECMS); 2) full knowledge of distance, upcoming terrain and estimated velocity (use D-ECMS and E-ECMS); 3) knowledge of distance to the next charging station and elevation changes (use B-ECMS); 4) no future information (use RB and DS-ECMS). In the first level, the optimal control minimizes the cost function to maximize fuel economy, the dynamic programming (DP) solves the problem according to Bellman's optimality principles and the ECMS finds the true value of equivalence factor, $s(t)$ by using Pontryagin's minimum principle. Second level estimates the velocity using real-time traffic data streams or historical traffic data. The D-ECMS calculates the cost-to-go of dynamic programming backward in time that depends on future power demands, and the E-ECMS iterates s value that yields the present SOC by running the ECMS backward and assuming final SOC_f equals to desired SOC_d (Figure 2.41). The third level uses blend ECMS (B-ECMS) to discharges battery gradually that depends on parameters of neutral equivalence factor s_0, electric mode equivalence factor s_e, current $SOC(t)$, and remaining trip distance. The optimal control without preview implements depleting and sustaining ECMS (DS-ECMS) with an equivalence factor increases if SOC decreases as shown in Figure 2.41. And in the rule-based (RB) control of the system is initially operated in all-electric CD mode if the power request is low, in blend mode if power request exceeds EM or battery capacity, and in charge sustaining (CS) mode when SOC is near its minimum allowable charge. Simulation of the control strategies show that DP can find the lowest energy cost and thus can be used as benchmark. The B-ECMS performance is close to D-ECMS and E-ECMS for a long distance route, but less performant at route with large elevation changes. The results show the advantages of information preview for fuel saving and the proposed algorithm is implementable for real-time

PHEV energy management.

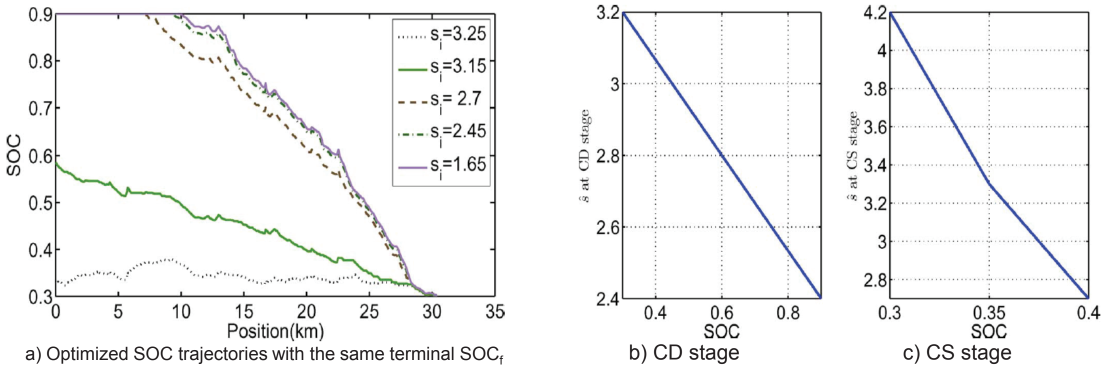


Figure 2.41: E-ECMS different initial guesses (s_i); a) Optimized SOC trajectories with the same terminal SOC_f, and DS-ECMS estimated $\hat{s}$ as a function of SOC at different stages; b) CD stage, and c) CS stage [28].

The control strategy plays a huge role in EV and HEV system. The complexity of these systems compared to a conventional ICE vehicle makes it important to manage its available energies optimally. The two methods that have been applied are the rule based method and the optimisation method. The rule based method is heuristic which is intuitive, and based on human experience and expertise. It is robust and has less computational load that makes it suitable for a real world application. It needs a good paremeter tuning to achieve optimal solution. The two approaches of this method are the deterministic rules and the fuzzy rules. The optimisation method tends to minimise a cost function globally or instantaneously. The global optimisation needs knowledge of the whole driving cycle known a priori and a precise components modeling of the system. It has huge computational burden and cannot be implemented online. It is global optimal and usually used as benchmark of other control strategies in development. The real time optimisation minimises a cost function instantaneously at each time step. It requires a short calculation time, and can thus be employed in real vehicle that demonstrates a nearly optimal behavior. The characteristics of each approaches are listed in table 2.2, the summary of the carried out researches are listed on table 2.3, table 2.4, table 2.5, and table 2.6.

2.5 Conclusion

There are so many methods that can be applied as control strategy depending on its utilisation. As a general conclusion, we can state that the energetic factor has accelerate the development of EV and HEV. Most of the objectives treated in the carried out researches are related to the fuel economy. Thereafter, comes the environmental preoccupation of the emissions factor

Rule-Based Method
Rules design is based on desirable outputs without any priori knowledge of a trip
Heuristics; based on engineering intuition and human expertise
Simple analysis on component efficiency tables
Easy to implement in real vehicle
Less computational load
Robust and effective
Not global optimal
Lack of formal generalization
Need a good parameter tuning

Optimisation Method
Can be local, global, real-time, parameter, or threshold optimisation
Use numerical and analytical method
Provide control design generality
Reduce control parameters heavy tuning
Consider all components efficiencies
Main task is to maximize or minimize a cost function

Table 2.2: Control strategies advantages and inconvenients.

Deterministic Rules
Operate on a set of rules, defined and implemented prior to actual operation
Utilize instantaneous operating condition as inputs
Based on analysis of power flow in a hybrid drive-train
The rules are implemented via lookup tables
The control response can be highly sensitive to inputs
[67], [18], [50], [51], [55], [79], [80], [19], [39], [81], [52], [72], [29]

Table 2.3: Deterministic rule based control strategies advantages and inconvenients.

Fuzzy Rules
Provide abstraction value of parameters
Tolerant to imprecise measurements and components variation
Ideal for nonlinear time-varying systems and multi-domain of hybrid power-train
The rules designed are limited to designers knowledge
Case sensitive and sometime difficult to tune
[22], [1], [15], [77], [71], [82], [83], [84], [85], [86], [87], [88]

Table 2.4: Fuzzy rule based control strategies advantages and inconvenients.

Global Optimisation
Optimization for the whole trip
Global optimal over a fixed driving cycle
Need knowledge of the entire driving cycle
Need information of the past and future events
Accurately know component conditions
Used for offline simulation
Large computational burden
Not implementable in real world application
Technological advances (GPS, e-maps, traffic data) make this approach implementable in real world application
Used as benchmark of other strategies
[90], [38], [91], [92], [30], [17], [20], [25], [93], [41], [37], [8], [42], [43], [94], [23], [95], [96], [4], [78], [74], [89], [44], [56], [76]

Table 2.5: Global optimisation control strategies advantages and inconvenients.

Real-time Optimisation
Minimize a cost function instantaneously, depend on the present variables
Have limited knowledge of future driving conditions and self-sustainability
Cost function is developed by past information
Adapt and optimize in real-time
Less computational burden
Can be applied in real vehicle
Solution nearly optimal
[97], [10], [75], [46], [47], [33], [48], [70], [68], [49], [14], [73], [9], [26], [7], [28]

Table 2.6: Real-time optimisation control strategies advantages and inconvenients.

Comparison criteria
1. Robustness
2. Optimality
3. Precision
4. Implementation
5. Calculation time
6. Deployment
7. Cost of deployment

	1	2	3	4	5	6	7
Deterministic Rules	⋆⋆⋆	⋆⋆	⋆⋆⋆	⋆⋆⋆	⋆⋆⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆
Fuzzy Rules	⋆⋆	⋆⋆	⋆⋆	⋆	⋆⋆⋆⋆	⋆⋆	⋆⋆⋆
Global Optimisation	⋆⋆	⋆⋆⋆⋆⋆	⋆⋆⋆	⋆	⋆	⋆⋆	⋆⋆
Real-time Optimisation	⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆	⋆⋆	⋆⋆	⋆⋆⋆	⋆⋆⋆

Table 2.7: Comparison of the methods.

with the aim to reduce feedgas and particulate matter emitted by the engine. On the system level, the motives are to achieve low running cost, have an optimal drive-train efficiency, and to meet traction power demand. Good drivability and smooth transition have been a focus of transmission systems for hybrid vehicles. The battery state of charge or health becomes one of the important elements considered in energy management in a vehicle system equipped with a relatively bigger battery capacity.

Controller design is different for each system, it depends on architecture, utilization, degree of hybridization, and targeted objectives. As can be observed, a series hybrid vehicle and a fuel cell/battery hybrid vehicle need a controller to manage power distribution between its power sources in form of the electrical energy. Contrary in a parallel hybrid and a series-parallel hybrid, the control is bounded to determine its torque split in form of mechanical energy to deliver requested power at wheels.

A good controller should yield an optimal solution, can be used in real vehicle, has good stability and sensitivity, can deliver demanded power, and can improve the efficiency of the system. Through table 2.3, table 2.4, table 2.5, and table 2.6, the advantages and inconvenients of each control strategy can be compared in order to choose a suitable controller according to the application. The carried out researches present the necessary development in control strategies due to up-to-date technological advance. These control methods are compared in table 2.7 to better compare the common criterias.

The rule based method is easy to implement and robust, but it is not easy to tune its control parameters manually to achieve an optimal solution. In most cases, simulation is conducted offline to determine the optimal parameter thresholds to be applied in the real vehicle. This can be done by using available standard cycles or past trip information. A good modeling of the vehicle system can represent closely the behavior and interaction between subsystems. In the global optimisation method, the complete trip/driving cycle must be known a priori to achieve an optimal solution. Eventhough it is not suitable for real world application, it can be used to optimise parameters or rules for other control strategies, or to compare the performance of a control strategy in development.

Challenges are what make life interesting and overcoming them is what makes life meaningful.

- Joshua J. Marine

Chapter 3

Modelisation Towards an Effective Model for HEV Series

3.1 Introduction

Hybrid electric vehicle (HEV) is regarded as one effective solution for the problem of energy shortage and demands to increase fossil fuel efficiency. The system which inherent advantages of improved fuel economy and reduced pollutant emissions, has higher fuel efficiency and can achieve better performance than a conventional vehicle [15, 14]. The presence of a reversible energy storage system (ESS) offers new degrees of freedom to deliver power, possibility of engine downsizing, idle-off, regenerative braking, and power assist that can increase the overall system efficiency [8, 7].

The design of HEV system architecture is complex, and the power management is complicated due to a high degree of control flexibility, as well as the use of non-linear and multi-domain components. Determination of design parameters and coordination of the multiple energy sources and converters to fully optimize its potential is cumbersome, time consuming, and expensive [58, 8, 10, 62, 64, 65]. Modeling of HEV configurations and interactions between its components becomes indispensable for rapid prototyping and analysis of HEVs.

HEV technology has been developed for many applications and different design combinations like series, parallel, and series-parallel. Series hybrid is the simplest kind of HEV and predominates urban transportation thanks to its outstanding transient performance and power response [14, 66, 15]. Low noise operation due to the use of electric motors alone for traction offers benefits particularly in military operations, but larger drive system and multiple energy conversions counteract the overall efficiency of this architecture [80].

HEV system models have been developed for diverse applications covering topics such as optimal design problems [60, 40, 62], subsystems interactions [40, 53], controller development

[58, 50, 98, 23, 80, 17], and system drivability [56]. Even if the models that can represent accurately a series HEV system exists, a model development of this system that focuses on a competition car is not yet available.

Two modeling methods will be utilised to model a hybrid race car called *Noao*. Results from drive test on racing circuit of the real car system will be used to validate the models. Firstly, a quasi-static model is developed to validate parameters and efficiency maps of the studied system, which also will be used for control strategy optimisation of the system.

And then, a development of this car model using dynamic method will be necessary to assess the performance of the car and to generate its driving cycle according to driver's input. Besides that, this type of model will be the platform to evaluate improvements due to changes that will be effected to this system, and to test a new optimal control strategy suitable for this system.

3.2 Noao Car

The *Noao* car is a plug-in series hybrid racing car (Figure 3.14) equipped with an engine/generator (E/G) set as range extender. This car is a result of collective work by experts and specialists of racing car around Magny-Cours circuit industrial site for racing track competition application [99, 100], where it becomes a reference for ongoing researches on HEV system.

The Association des Entreprises Pole de la Performance Nevers Magny-Cours and Magny-Cours Circuit use their expertise and experiences to build the car shown in Figure 7.2 and heuristically define its control algorithm.

The vehicle architecture is presented in Figure 7.3 with arrows direction correspond to power flow in the system. The power-train is composed of an electric traction motor (EM), a power converter (PC), a battery pack (B), and a set of range extender consisting of an internal combustion engine (ICE) and a generator (G).

The vehicle component parameters are depicted in table 7.1. Detailed characteristics of this car can be found in the website of the association [99]. The prime mover is a permanent magnet synchronous machine (PMSM) electric motor, acts as motor during traction and as generator during regenerative braking. The internal combustion engine is a gasoline engine with a 998 cm^3 displacement volume.

Three identical battery packs serve as the reversible energy storage system (ESS), provide most of the energy needed for propulsion and energy recuperation during regenerative braking. The engine/generator (E/G) set generates power for the range extender path. Both power sources are connected to an electric power bus which is connected to the electric motor power converter.

Figure 3.1: Noao racing car.

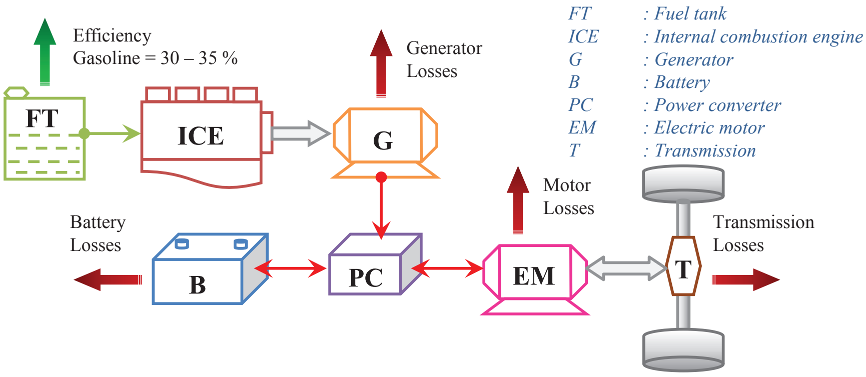


Figure 3.2: Architecture of the series hybrid.

Table 3.1: Vehicle parameters for Noao

Vehicle mass, m_v	1200 kg
Front area, A	2 m^2
Drag coefficient, C_x	0.35
Rolling resistance, μ	0.012
Wheel diameter, d_w	0.62 m
Engine	3 cylinders 1.0 L, direct injection
Generator	54 kW at 4500 rpm, 120 Nm
Electric motor	280 kW peak power, 800 Nm
Battery	3 Lithium-ion batteries, 520 V
Transmission	Simple, ratio 2.9, efficiency 0.95

3.2.1 Actual Control Strategy

The energy management method used in the original car is a rule based control strategy, chosen because of its simplicity and its large utilisation in demonstrator vehicles. It is a heuristic method and the determination of its parameter thresholds are based on observation of the requested power.

Based on a documentation of the range extender control [101], three subsystems control are defined to control the range extender part; the mode control, the sequence control, and the speed control through D-Space application.

The mode control handles the training, race, or fire-up mode which defines the conditions to allow the range extender to start. This subsystem control takes car velocity, traction power, SOC, and other fifteen parameters related to temperature and current as inputs to output the target powers.

The outputs are then evaluated to define five states in the control sequence; off, cranking, ramps up, charging, and ramp down to determine the mass of fuel to be injected in the engine to produce the torque needed at both ICE and generator.

And then, using a feedforward PI controller, the speed control determines the requested torque according to the speed target defined by the sequence control.

Like in its real system, similar parameters like the traction power needed at wheel and the battery SOC will be taken as inputs of the range extender for simulations of this car system.

3.3 Quasi-static Model

A quasi-static model is a noncausal model, where its inputs and outputs are not fixed. This kind of model consists of a steady-state model to which an equivalent dynamic model of the system is added [54]. Like in an engine, it associates a map and a first-order of the system to form the model.

In this study it is used to determine the systems component characteristics and parameters. This is done by comparing the results from the experiments and the simulation component by component. This model is useful in a numerical solution that has a big computation burden, because it uses a bigger and slower timestep for the modelisation.

As can be seen in Figure 7.4, the power request is obtained starting from the driving cycle. It is a backward simulation method [54], from a vehicle velocity up to engine and battery to calculate the system's energy consumption. The model is simple and easier to build, but it did not represents exactly the behavior of the system like in its real system.

For the studied system, the equations used to model the whole system are based on a complete documentation of [102]. Efficiencies of the power converters are presented in Figure 3.4 and Figure 3.5, implemented via lookup tables in the simulation.

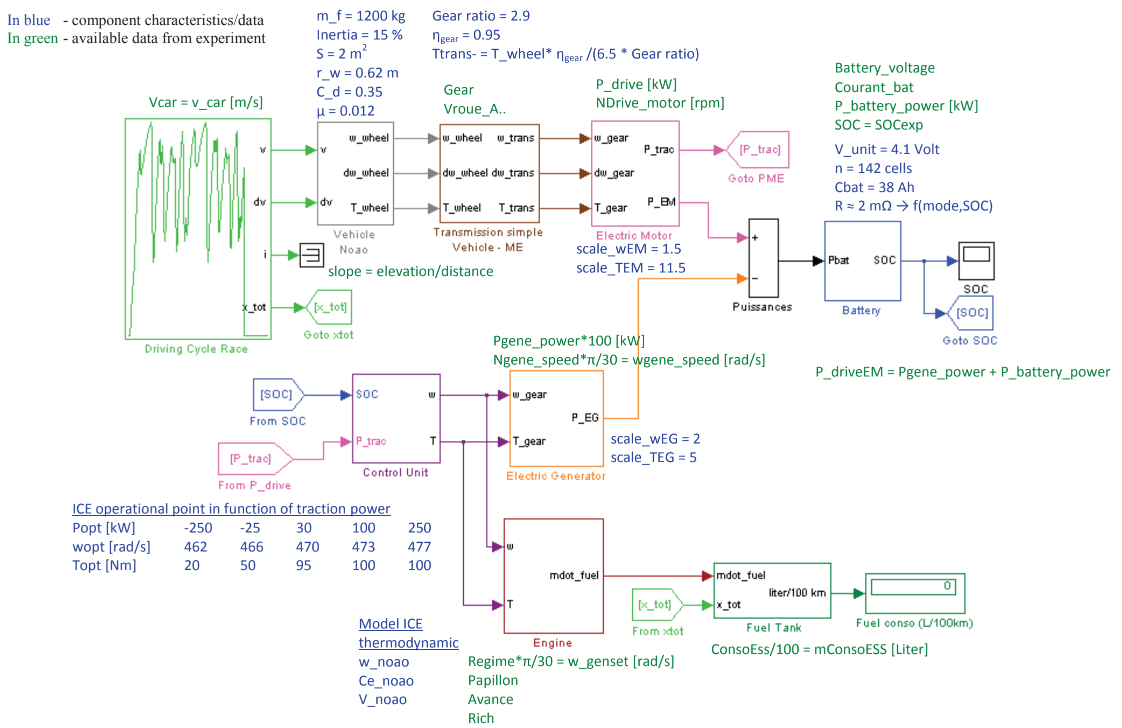


Figure 3.3: Modelisation of the Noao car using quasi-static modeling method.

The brake specific fuel consumption (BSFC) and the efficiency map of the engine is presented in Figure 3.6. The method to obtain these maps is explained in the next subsection.

3.3.1 Energy Sources Modelisation

Battery Model

The primary energy source of this system is the battery. There are three identical lithium-ion batteries with 520 V nominal voltage installed in this car. The batteries are identical to each other in order to have the same SOC performance. They are connected in series and placed in the vehicle to balance the weight distribution of the car [99, 100]. The model of the battery is represented by (3.1), (3.2), (3.3), and (3.4).

$$P_{bat} = i_{bat} \cdot V_{\Sigma bat} \tag{3.1}$$

$$SOC = SOC_{initial} - \frac{\int i_{bat} \cdot V_{\Sigma bat}}{C_t} \tag{3.2}$$

P_{bat} is the power to the battery in W, it is positive during discharge and negative if it is recharged. SOC is defined as the index of the current energy available from a battery compared

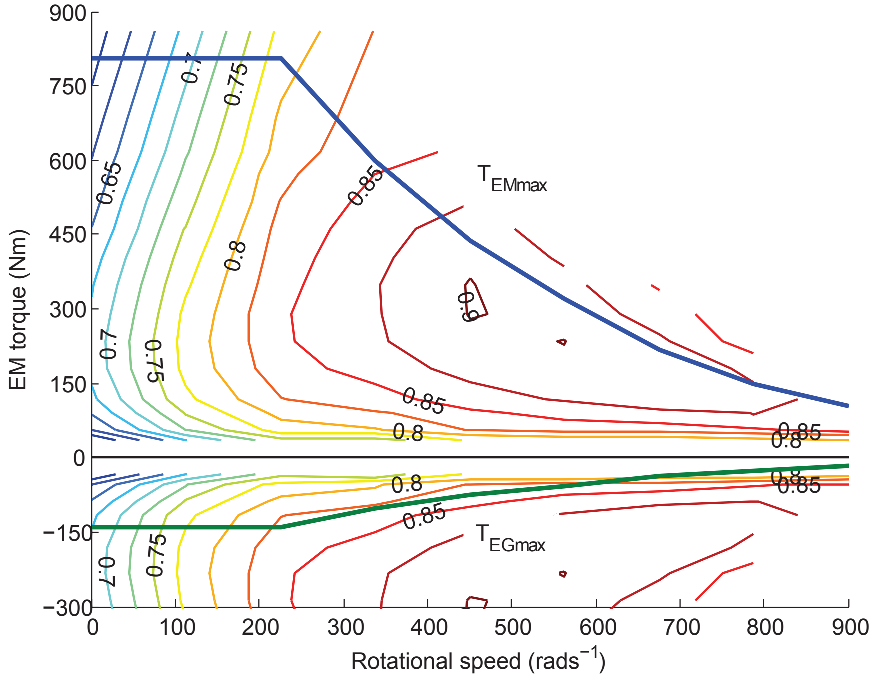


Figure 3.4: Electric motor efficiency map of the Noao car.

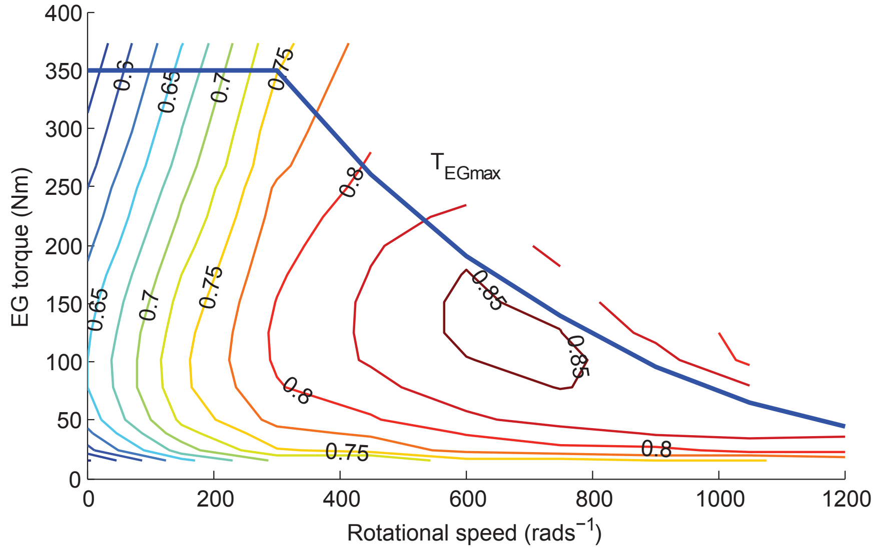


Figure 3.5: Electric generator efficiency map of the Noao car.

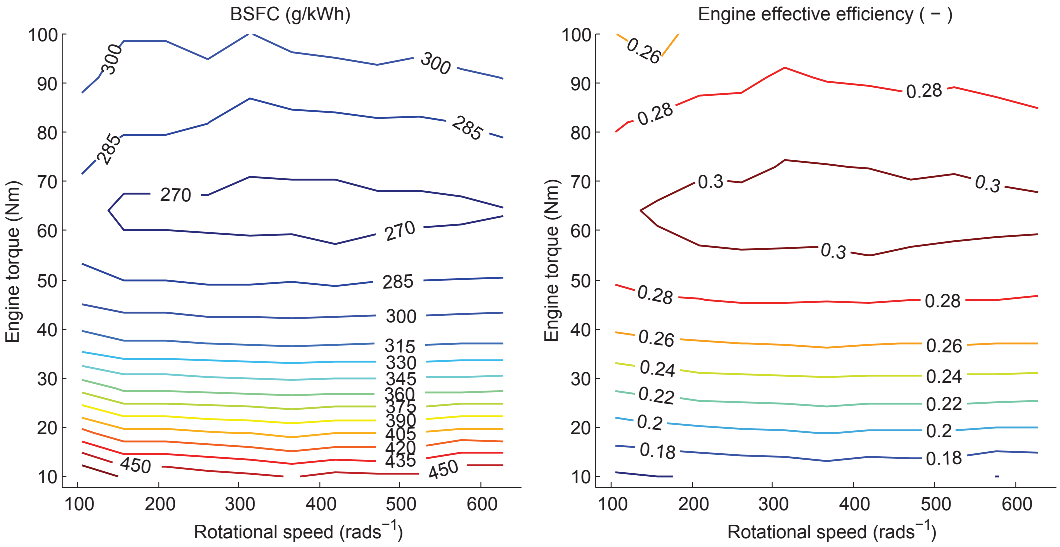


Figure 3.6: Internal combustion engine efficiency map of the Noao car.

to the battery capacity C_t (Wh). And the voltage of the battery package $V_{\Sigma bat}$ (V) is the cell voltage V_{bat} (V) times the number of cells in the battery pack, with the current of the battery i_{bat} in A.

$$V_{OC} = -1.031\exp(-35SOC) + 3.685 + 0.2156SOC - 0.1178SOC^2 + 0.321SOC^3 \tag{3.3}$$

$$V_{bat} = V_{OC} - R \cdot i_{bat} \tag{3.4}$$

The battery open circuit voltage V_{oc} (V) and resistance R (Ω) are in function of SOC and its mode i.e charge or discharge. Resistance of a lithium-ion battery is known to be the lowest around 0.002 Ω which resistance values are shown in Figure 3.7 for one cell of this battery.

Internal Combustion Engine Model

The internal combustion engine (ICE) is the other main component inside the system, as it will determine the fuel consumption of the vehicle. This fuel consumption is closely linked to the ICE efficiency (3.5), η_i is defined as the ratio between the work transfer to the piston thanks to the in-cylinder pressure and the theoretical energy available in the fuel. Pressure P is in Pa, dV is the displaced volume in m^3, and m_{fuel} is in kg.

$$\eta_i = \frac{\int -PdV}{m_{fuel}LHV} \tag{3.5}$$

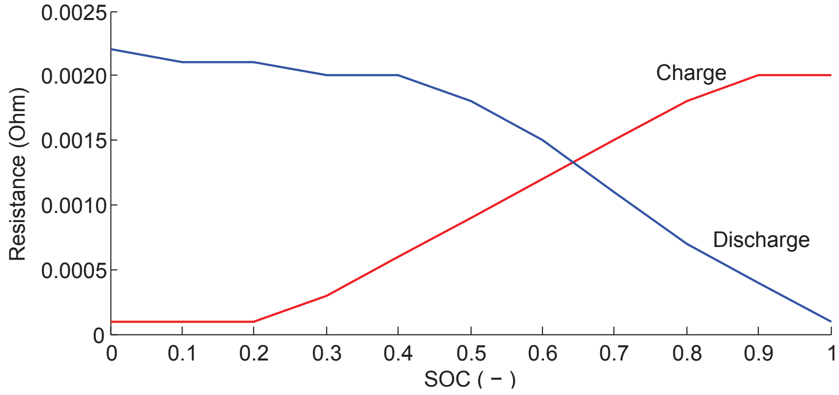


Figure 3.7: Resistance of the battery in function of SOC and its mode.

An approach of zero-dimensional single-zone thermodynamic model is used to determine the ICE efficiency for this model [103, 104]. This approach can evaluate the influence of the engine speed and load on the fuel indicated efficiency.

The cylinder is considered as an open system where pressure, temperature, and mixture composition are homogeneous. The gas is supposed to be a constant mixture of fuel and air. The model is governed by the conservation of mass and the conservation of energy. The cylinder can only exchange mass through the intake and exhaust valves (3.6).

$$\frac{dm}{dt} = \frac{dm_{int}}{dt} + \frac{dm_{exh}}{dt} \tag{3.6}$$

where m is the mass inside the cylinder and dm_{int}/dt (respectively dm_{exh}/dt) is the mass flow rate through the intake (respectively exhaust) valve.

The first law of thermodynamics is applied to the open system which exchanges heat through the wall Q_{wall} and receives heat thanks to a combustion model Q_{comb}. The work transfer through the piston due to the change of in-cylinder volume, V is equal to $-PdV/dt$ (3.7).

$$\frac{dmu}{dt} = \frac{dW}{dt} + \frac{dQ}{dt} = -P\frac{dV}{dt} + \frac{dQ_{wall}}{dt} + \frac{dQ_{comb}}{dt} \tag{3.7}$$

where u is the internal energy.

Since, the unknowns are the pressure, the temperature and the mass inside the cylinder a third equation is needed which is the ideal gas law in its derived form (3.8).

$$P\frac{dV}{dt} + V\frac{dP}{dt} = \frac{dm}{dt}rT + m\frac{dr}{dt}T + mr\frac{dT}{dt} \tag{3.8}$$

where r is the ideal gas constant $r = R/M$ since the mixture composition is constant $dr/dt = 0$.

Therefore, some models are needed in order to calculate the mass flow rate through the valve, the heat exchange with the wall and the heat release from the combustion process.

The mass flow rate is calculated with the assumption of the quasi-steady adiabatic and compressible flow. The flow is generated due to the difference in pressure between the upstream (us) and the downstream (ds) if $P_{us} \geq P_{ds}$. Thus, mass flow rate depends on the upstream conditions (pressure P_{us}, temperature T_{us}) and the downstream pressure, P_{ds} (3.9).

$$\frac{dm}{dt} = AC_d P_{us} \sqrt{\frac{2\gamma}{(\gamma-1)rT_{us}}(X^{\frac{2}{\gamma}} - X^{\frac{\gamma+1}{\gamma}})} \tag{3.9}$$

where

$$X = \frac{P_{ds}}{P_{us}} \leq (\frac{2}{\gamma+1})^{\frac{\gamma}{\gamma-1}} \tag{3.10}$$

The heat exchange with the wall is considered to be forced convection (3.11) and the heat transfert coefficient is calculated thanks to the correlation defined by Han et al. [105, 106].

$$\frac{dQ_{wall}}{dt} = hS(T - T_{wall}) \tag{3.11}$$

Finally, the heat release rate, dQ_{comb}/dt, is calculated thanks to the empirical burning law defined by Wiebe [105, 106] which is commonly used [105] in internal combustion engines thermodynamic model. This law (3.12) considers an exponential evolution of the heat release from the combustion, starting at θ_i crank angle degree before the top-dead-center with a combustion duration of $\Delta\theta$.

$$Q_{comb} = m_{fuel} LHV(1 - e^{-a(\frac{\theta-\theta}{\Delta\theta})^{n+1}}) \tag{3.12}$$

Here, given a simplified approach capable to describe the approximative fuel consumption in function of the cylindric volume V_d in m^3, rotational speed N in rpm, and delivered power P_e (W) as in (3.13).

$$\dot{m}_f = \frac{P_e + (f + f_p N)\frac{V_d N}{R_c 60}}{\eta_i(\eta_{c0} - \frac{A}{B+N})LHV} \tag{3.13}$$

with $\dot{m}_f$ the mass flow of the fuel in kgs^{-1}, f the friction factor assumed to be 100 kPa, f_p the friction factor of 20, the factor R_c equal to 1 for two-stroke motors and 2 for four-stroke motors. The fuel indicated efficiency η_i is assumed to be constant 0.4, in reality this factor is varying due to operating point. The combustion efficiency is evaluated using the constant term η_{c0} assumed to be 0.98 and $A/(B + N)$ with A equal to 300 and B equal to 2000 respectively and LHV (Jkg^{-1}) is the lower heating value of the fuel used.

3.3.2 Model Validation

Two different driving cycles obtained from drive tests of the Noao car are used to verify the model. The results from these experiments are compared to the simulation results presented in Figure 3.8 for the traction part comprising the wheel and electric motor, Figure 3.9 for the battery, and Figure 3.10 for the electric generator and engine.

Referring to Figure 3.8, the first driving cycle at the beginning of the graph, noted as MC1 timed from 240 s to 850 s has a maximum speed of 42 ms^{-1} and the second driving cycle, MC2 time is from 1700 s to 2400 s with a maximum vitesse of 48 ms^{-1}. There is a slight difference in the wheel rotational speed because the comparison are made only with the left front wheel of the vehicle. The MC1 and the MC2 are conducted at the same Grand Prix circuit but with a higher given power for MC2 with 100 kW maximum power and 350 Nm maximum torque, while it is only 82 kW and 300 Nm for MC1. But the limits for regenerative braking is 25 kW, same for both MC1 and MC2.

Some current overshoot can be seen from the model in Figure 3.8. Nevertheless, the model is quite accurate with errors are limited under 5 % for the current, voltage, and SOC of the battery. A big difference in voltage and SOC occur during the no-current state.

In Figure 3.10, the range extender has to supply 40 kW during traction and down to 20 kW whenever it is in regenerative braking mode for both driving cycles MC1 and MC2. The range extender rotational speed is constant at 470 rads^{-1}, the additional power is applied as torque with 80 Nm for traction, and then 40 Nm during the recuperation energy. Fuel consumption of the engine in liter is represented correctly by the model.

Eventhough this model is just a structural model in which inputs and outputs can be chosen based on device to device association, this model development is important for a system level global energy management to coordinate the power flow of each subsystems and in supervising the whole system.

3.4 Dynamic Model

Dynamic models take into account transient states in a real time control of power flows. A local energy management must be ensured in real time, so it is essential to understand the function of each subsystems according to the physical causality like in a causal model to prevent risk of damage and inefficient operation.

A causal model uses the principle of cause and effect to describe the system's behavior. In some devices, it has a fixed output which is an integral function of the input with an induced delay time. There are many graphical formalisms that can be used to represent multiphysics and complex system such as Bond Graphs, Power Oriented Graphs, Power Flow Diagrams, Causal Ordering Graphs, and Energetic Macroscopic Representation.

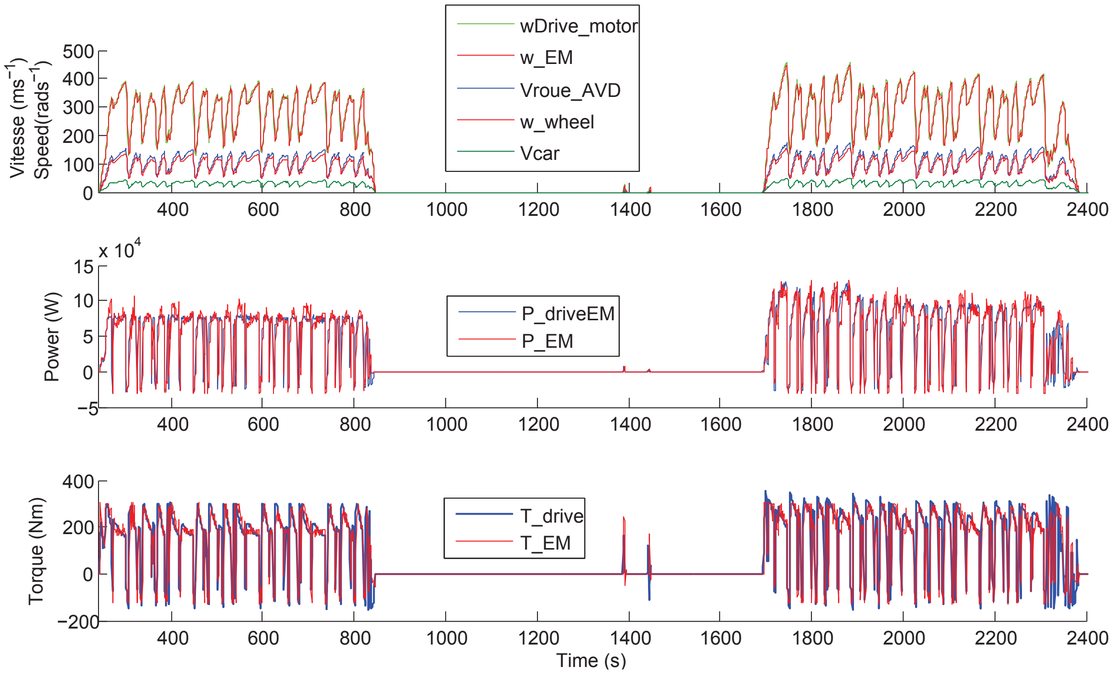


Figure 3.8: Verification of the traction model; chassis, wheel, and electric motor of the Noao car using quasi-static modeling method.

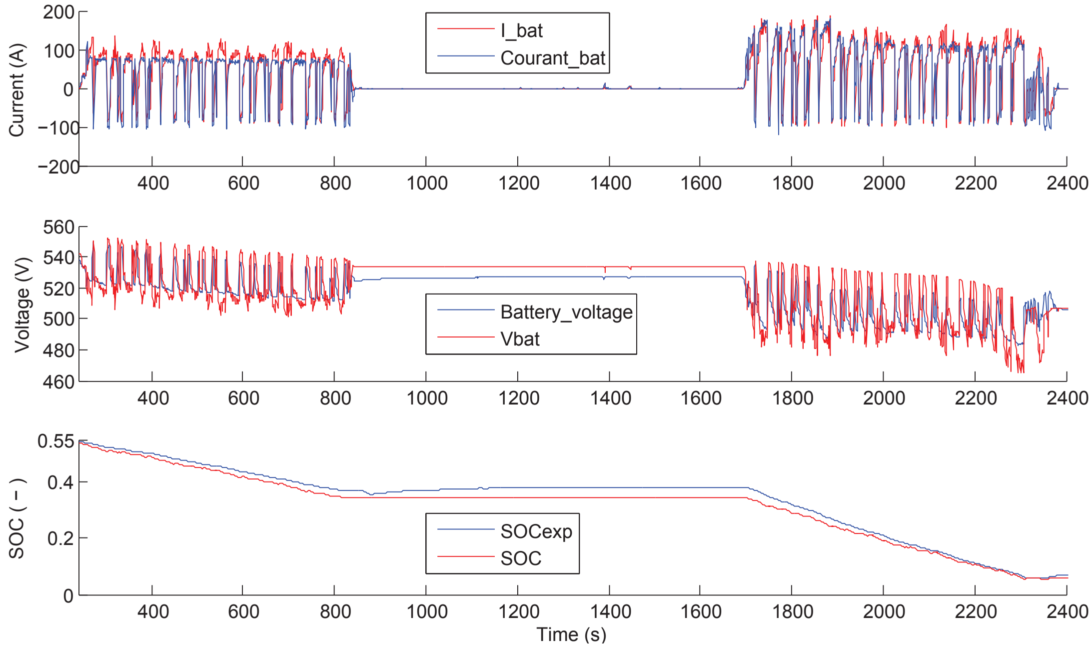


Figure 3.9: Verification of the battery model of the Noao car using quasi-static modeling method.

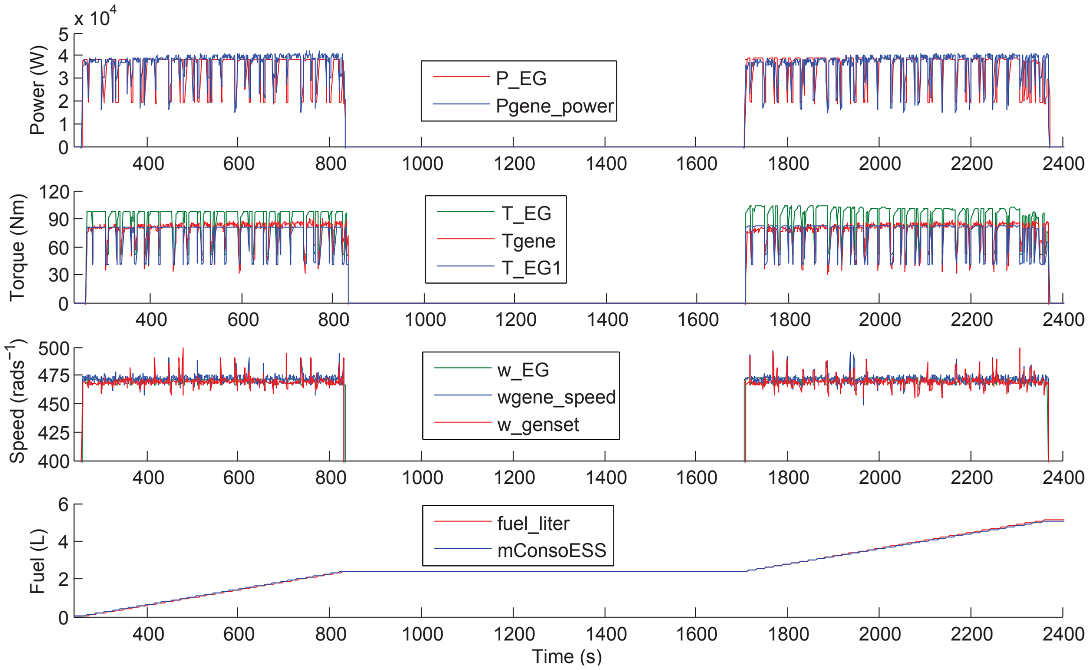


Figure 3.10: Verification of the engine and generator model of the Noao car using quasi-static modeling method.

3.4.1 Energetic Macroscopic Representation

Energetic Macroscopic Representation (EMR) is a causal approach for dynamic simulation, with the goal to develop control structures based on a separation of complex systems into sub-blocks. This methodology has already been used successfully for multi machine applications [107], fuel cell systems [108], but also electric vehicle traction [63, 64, 65, 109, 110].

The overall architecture of the EMR model including all components and control blocks for the *Noao* racing series hybrid car is presented in Figure 7.6. The green oval blocks are the source of energy, orange blocks are the converters, and the blue blocks are the control blocks. A block with a croosbar is an element with energy accumulation and doubled block is a coupling device [63, 65, 64, 111]. A monophysical domain converter is square and a multiphysical domain converter is round. The recent synoptic of the EMR is included in [112].

All vehicle components are integrated together in a functional description based on the action reaction principle of the power flow. EMR allows a system to be synthetically described. Modeling using this description allows us to develop a control structure and highlights the controllers, pertubation rejections, and the necessary estimations [113].

EMR of this car is based on representation made in [110] where the battery and the power converter are combined to form the equal electrical source (ESeq) for the traction part of the

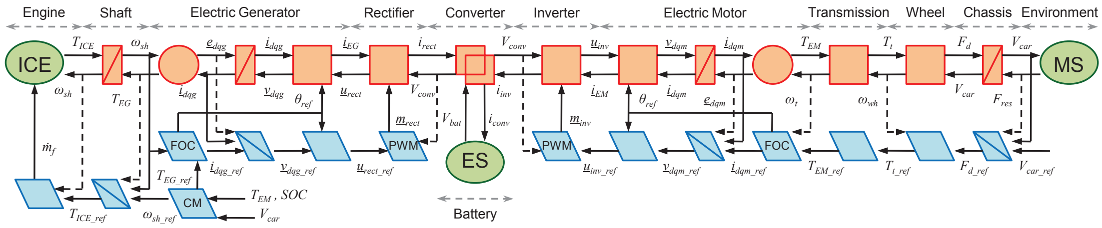


Figure 3.11: Energetic Macroscopic Representation of the car system and its control scheme.

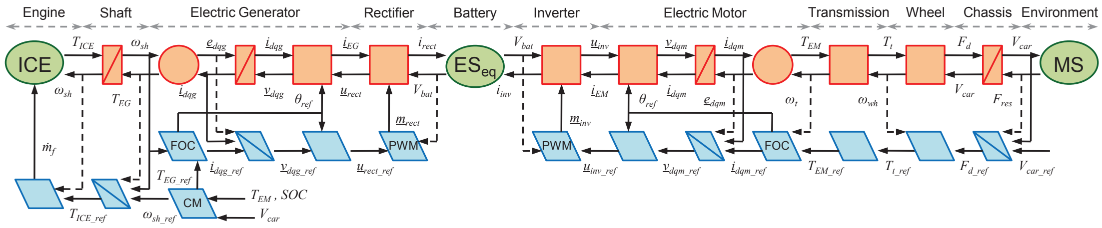


Figure 3.12: Energetic Macroscopic Representation of the car system and its control scheme with the equivalent electrical source.

system. Before that, the appropriate representation is depicted in Figure 7.5.

Mechanical Source

The system environment is taken as the mechanical source (MS) of the system that gives resistance or potential force towards the car movement, F_{res}.

This powertrain losses consist of the aerodynamic resistance F_a, the rolling resistance F_r, and the hill climbing force due to a non-horizontal roads F_g (3.14). The hill climbing force F_g of the vehicle is positive in uphill and negative if it is in downhill. For the Magny-Cours racing circuit, this α (3.15) element can be included in the analysis by using the road elevation information available for the circuit in [100] and as shown in Figure 3.13.

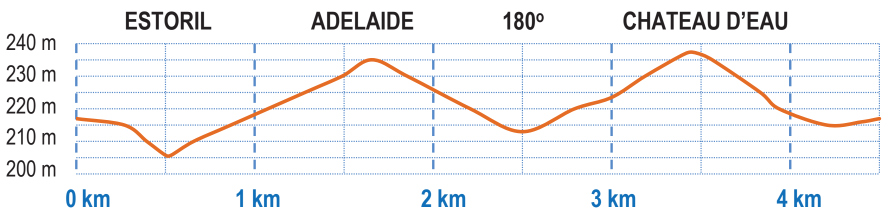


Figure 3.13: Road elevation of the Magny-Cours circuit.

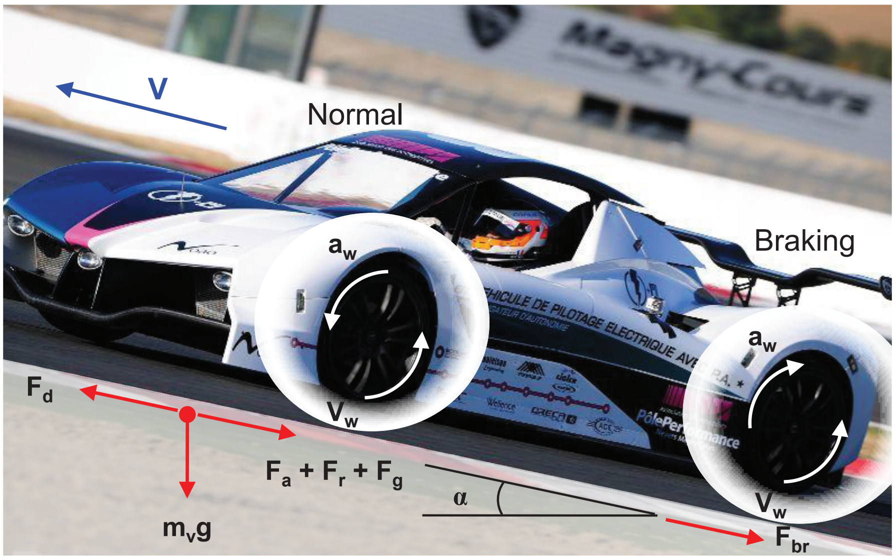


Figure 3.14: Noao car.

$$F_{res} = F_a + F_r + F_g \tag{3.14}$$
$$= \frac{1}{2}\rho A C_x + \mu m_v g + m_v g sin(\alpha) \tag{3.15}$$

Where the forces F_{res}, F_a, F_r, and F_g are in N, gravity g in ms^{-2}, and the vehicle mass m_v in kg. A (m^2) is the car front surface, air density ρ is in kgm^{-3}, C_x is the drag coefficient, and μ is the rolling coefficient.

Chassis Model

The longitudinal dynamic derived from Newton's Second Law to determine the velocity of the vehicle V_{car} (ms^{-1}) is described in (3.16). The force to accelerate the vehicle and the rotating parts inside the vehicle is equal to the available driving force F_d, generated by prime mover minus the total resistance forces F_{res} (Figure 3.14).

$$(m_v + m_r)\frac{d}{dt}V_{car} = F_d - F_{res} \tag{3.16}$$

Equivalent mass of rotating parts m_r from the electric motor down to the wheels to determine the inertial force to accelerate rotating parts inside this car [35] are detailed in (3.17) and added into the mass of the vehicle during normal driving. Calculation reveals 185 kg rotational mass for mechanical efficiencies η_f and η_t of 0.95, final gear ratio i_f of 1, transmission ratio i_t of 2.9, and polar moment of inertia of 3.2 kgm^2, 0.05 kgm^2, and 1.8 kgm^2, for the wheels I_w, propeller shaft I_p, and electric motor I_{em} respectively.

$$m_r = (\frac{1}{r_w})^2[I_w + I_p\eta_f {i_f}^2 + I_{em}\eta_t(i_f i_t)^2] \tag{3.17}$$

During braking, to slow down the car, an external negative braking torque is applied to the wheel. It is the sum of the motor regenerative braking torque and the system supplementary mechanical braking torque [62]. Driving force F_d is replaced by the braking force F_{br}. The wheel linear speed becomes less than the vehicle speed and creates an opposite force to the forward motion. In this phase, the traction force caused by the friction between the road surface and the tire surface, is the weight dynamic transfer times the adhesive coefficient μ [5, 62] expressed in (3.18) and (3.19). The adhesive coefficient μ is a function of slip ratio λ under certain tire condition and road conditions.

$$(m_v + m_r)\frac{d}{dt}V_{car} = F_{br} - F_{res} \tag{3.18}$$

$$= \mu(\lambda)m_v g - F_{res} \tag{3.19}$$

As for the studied system, the driving test is performed on a dry asphalt track. At acceleration to braking transition illustrated in Figure 3.14, the rotating mass accelerate in the inverse direction (a_w) of the vehicle linear speed V, resulting less dynamic weight transfer to the vehicle during this phase.

Lateral motion equation to calculate lateral force is not included because the exact steering angle measurements are not available from the experiment. Only one wheel is taken into consideration here, which eliminates the possibility to study drifting effects. A modeling of yaw rate effect for a sport series HEV can be found in [114].

Wheel, Transmission, and Shaft Model

At wheel, the driving force F_d is a function of the transfered transmission torque T_t in Nm and r_{wh}, the wheel radius in m (3.20). And the wheel speed ω_{wh} (rads^{-1}) depends on V_{wh} (ms^{-1}), the linear speed of the wheel (3.21).

$$F_d = T_t/r_{wh} \tag{3.20}$$

$$\omega_{wh} = V_{wh}/r_{wh} \tag{3.21}$$

For a series hybrid configuration [65, 110, 63], T_{EM} (Nm) (3.22) and the ω_t (rads^{-1}) (3.23) is transfered through a fixed transmission ratio, with r_g the gear ratio and η_t the transmission efficiency.

$$T_t = \eta_t r_g T_{EM} \tag{3.22}$$

$$\omega_t = r_g \omega_{wh} \tag{3.23}$$

The shaft rotational speed ω_{sh} (rads^{-1}) is obtained from torque value in Nm of the engine T_{ICE} and the generator T_{EG}. J is the shaft moment of inertia in kgm^{-2} and f is the shaft friction coefficient.

$$J\frac{d}{dt}\omega_{sh} + f\omega_{sh} = T_{ICE} - T_{EG} \tag{3.24}$$

Electric Motor and Electric Generator Model

Both the electric motor and the generator of the Noao are permanent magnet synchronous machines (PMSM) described in order to apply vector control based on [115] by the following approach:
The torque T_e (Nm) developed by the machine is evaluated from system parameters and Park transformed currents (3.25).

$$T_e = 1.5p[\lambda_f i_q + (L_d - L_q)i_d i_q] \tag{3.25}$$

where i_d is the direct axis component of the stator current (A) and i_q is the quadrature axis component. The inductances (H) of the stator is L_d for the direct axis and L_q for the quadrature axis. Permanent magnet flux linkage is λ_f (Wb) and p is the stator pole pairs per phase. From this, torque friction losses T_f (Nm) are excluded (3.26) based on method defined in [116].

$$T_{EM} = T_{EG} = T_e - T_f \tag{3.26}$$

The electromotive forces e (V) are evaluated according (3.27) and (3.28). Its angular frequency ω_e (rads^{-1}) is equal to $p\omega_r$, with ω_r (rads^{-1}) is the rotor speed.

$$e_d = L_q i_q p\omega_r \tag{3.27}$$

$$e_q = (L_d i_d + \lambda_f)p\omega_r \tag{3.28}$$

And the link between current and electromotive force for direct and quadrature axis can be explained by (3.29) and (3.30).

$$L_d\frac{d}{dt}i_d + Ri_d = v_d + e_d \tag{3.29}$$

$$L_q\frac{d}{dt}i_q + Ri_q = v_q - e_q \tag{3.30}$$

Inverter and Rectifier Model

To drive the traction motor, a three phase inverter is used. It can be described by a simplified approach including a modulation vector $\underline{m}_{inv}$ defined from the switching functions [117, 109]. It yields the output amplitude in function of the input amplitude and is transposed $\underline{m}_{inv}^{t}$ for the currents (3.31), (3.32).

$$\underline{u}_{inv} = \underline{m}_{inv} V_{bat} \tag{3.31}$$

$$i_{inv} = \underline{m}_{inv}^{t} \underline{i}_{EM} \tag{3.32}$$

The generator output is rectified in order to supply the ICE energy to the dc bus, therefore a three-phase full bridge controllable rectifier is used in order to be able to adapt the output voltage to the bus voltage as described in (3.33) and (3.34).

$$\underline{u}_{rect} = \underline{m}_{rect} V_{bat} \tag{3.33}$$

$$i_{rect} = \underline{m}_{rect}^{t} \underline{i}_{EG} \tag{3.34}$$

Lithium-Ion Battery Model

The battery is a crucial element inside a hybrid vehicle, its correct description is important especially with regard to cooling [118] and aging [119]. In our case the focus is put on the development of a global control structure. EMR methodology allows an upgrade of dedicated sub-models, like the battery model, without the need to change the rest of the model.

In this model, the battery model is considered as an electrical source for the traction part and is assumed to be the equivalent electrical source (ESeq) to the charge part [110]. Thus, the battery current i_{bat} (A) is considered as the total current entering or exiting the battery by inverter i_{inv} (A) and rectifier i_{rect} (A) (3.35). And the battery voltage V_{bat} (V) is V_{conv} (V) (3.36).

$$i_{bat} = i_{conv} = i_{inv} - i_{rect} \tag{3.35}$$

$$V_{bat} = V_{conv} \tag{3.36}$$

Internal Combustion Engine Model

Finally, the torque T_{ICE} (Nm) can be evaluated from the value of the injected fuel $\dot{m}_f$ (kgs^{-1}) and the efficiency η_i determined before in its quasi-static model (3.37).

$$T_{ICE} = \frac{\eta_i \dot{m}_f LHV - P_{fr}}{\omega_{sh}} \tag{3.37}$$

Where P_{fr} in W is the ICE friction loss, LHV in Jkg^{-1} is the lower heating value of the fuel used, and ω_{sh} in rads^{-1} is the shaft rotational speed.

3.4.2 Inversion Based Control

The EMR goal is to provide a simple method to develop an inversion based control strategy for complex, multi-physics systems. The control structure is developped by a block wise inversion of the system model, where integral blocks and split or connection blocks require the most attention [107, 64, 111].

Using IBC method, each EMR elements of the tuning chain are inversed to deduce the control chain [110, 63]. The converter blocks like the transmission can be simply inverted (3.38), but a criterion input is required for inversion of the coupling devices [109].

$$T_{EM\_ref} = \frac{T_{t\_ref}}{\eta_t r_g} \tag{3.38}$$

During braking, the driving force becomes the braking force, where the torque on the wheels has to be split between regenerative braking and mechanic braking due to limits of the regenerative system (3.39).

$$T_{t\_ref} = F_{d\_ref} r_{wh} = F_{br\_ref} r_{wh} \tag{3.39}$$

Elements described by integral relationship such as the chassis (3.40), the electric motor or the electric generator accumulator (3.41), (3.42), and the range extender shaft (3.43) require a controller C to invert them.

$$F_{d\_ref} = C[V_{car\_ref} - V_{car}] + F_{res} \tag{3.40}$$

$$\underline{v}_{dqm\_ref} = C[\underline{i}_{dqm\_ref} - \underline{i}_{dqm}] + \underline{e}_{dqm} \tag{3.41}$$

$$\underline{v}_{dqg\_ref} = C[\underline{i}_{dqg\_ref} - \underline{i}_{dqg}] + \underline{e}_{dqg} \tag{3.42}$$

$$T_{ICE\_ref} = C[\omega_{sh\_ref} - \omega_{sh}] + T_{EG} \tag{3.43}$$

The electric motor and generator converters are both controlled by a field oriented control (FOC) [115, 109, 64, 116], requiring the measurement of the rotational speed and the actual rotor position by a rotor position sensor to determine the rotor position θ_{ref} and to deduce the flux reference ϕ_{r_ref}. In (3.44) and (3.45), the quadrature axis current i_{q_ref} is proportional by k to the electromagnetic torque if the direct axis current i_{d_ref} is forced to zero.

$$\underline{i}_{dqm\_ref} = \frac{T_{EM\_ref}}{k\phi_{r\_ref}} \tag{3.44}$$

$$\underline{i}_{dqg\_ref} = \frac{T_{EG\_ref}}{k\phi_{r\_ref}} \tag{3.45}$$

Inversion of the transformation function T yields the reference voltage $\underline{u}_{ref}$ from the dq voltage (3.46), (3.47). This inversion need the θ_{ref} to inverse the Park Transformation function.

$$\underline{u}_{inv\_ref} = [T(\theta_{ref})]^{-1}\underline{v}_{dqm\_ref} \tag{3.46}$$

$$\underline{u}_{rect\_ref} = [T(\theta_{ref})]^{-1}\underline{v}_{dqg\_ref} \tag{3.47}$$

The continuous modulation functions $\underline{m}$ need measurement of the battery voltage V_{bat} (3.48), (3.49), and are converted to discrete variables using a pulse width modulation (PWM) in order to define commutation orders of the switches [117, 109].

$$\underline{m}_{inv} = \frac{\underline{u}_{inv\_ref}}{V_{bat}} \tag{3.48}$$

$$\underline{m}_{rect} = \frac{\underline{u}_{rect\_ref}}{V_{bat}} \tag{3.49}$$

The charge management (CM) is determined by values of the car velocity V_{car} (3.50), the motor torque request T_{EM}, and the estimated battery SOC like in its actual control strategy [110, 64] as depicted in Figure 7.6. The SOC is used to weight the demanded power in order to supply a constant power if the battery voltage drop when the charge depletes (3.51).

$$\omega_{sh\_ref} = f(V_{car}) \tag{3.50}$$

$$T_{EG\_ref} = f(T_{EM}, SOC) \tag{3.51}$$

The amount of fuel to be injected in the engine $\dot{m}_f$ in order to meet the range extender power demand is controlled by the determination of the desired torque T_{ICE_ref} and instantaneous value of the engine shaft speed ω_{sh} (3.52) [104].

$$\dot{m}_f = \frac{T_{ICE\_ref}\omega_{sh} + P_{fr}}{\eta_i LHV} \tag{3.52}$$

3.4.3 Dynamic Model Validation

Model Validation

For validation, the model results are compared to experimental results obtained from measurements obtained during drive test on the Magny-Cours Grand Prix race track of 610 s timed from instant 240 to 850 s, for 4 laps of 4.411 km each, the MC1. The driving cycle as well as the power and torque provided by the electric propulsion motor are presented in Figure 3.15.

In general it can be seen, that the power and torque demand evaluated by the model is in good accordance with the measured values, only high accelerations at the beginning of the race lead to some overshoots.

The origin of these discrepancies are maybe caused by the frequence of the model chosen for the simulation. In this simulation, the timestep taken is less than 0.005 s, and from observation these disparities will be more if the timestep is smaller. This also maybe caused by the simplicity of the model which only consider the basic formulation of the system without including any filter method.

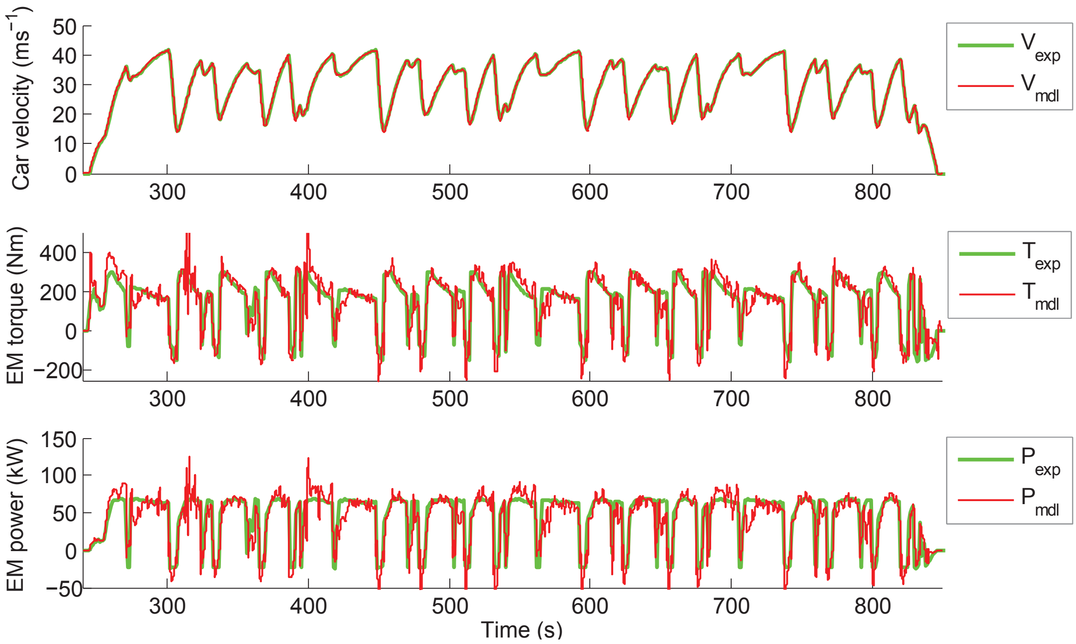


Figure 3.15: Driving cycle and profiles of power and torque at the electric motor.

The data of battery validation are presented in Figure 3.16, they show good accordance of the model with regard to the battery currents, voltages, and SOC. At abrupt load changes the model underestimates the minimum currents for energy recovery, this discrepancy disappears if the duration of the energy recovery is longer. Furthermore, it can be seen that the experimental battery voltage seems to be limited to 520 V, this might be due to a battery management system, that is not yet represented in the model.

The engine generator starts shortly after the beginning of the race and stays at a constant high rotational speed. The torque is put to a constant high value, this value is reduced during regenerative braking in order to respond to the maximum recharge current that can be accepted by the battery (Figure 3.17). This behavior is correctly represented by the model as well as the integrated fuel consumption.

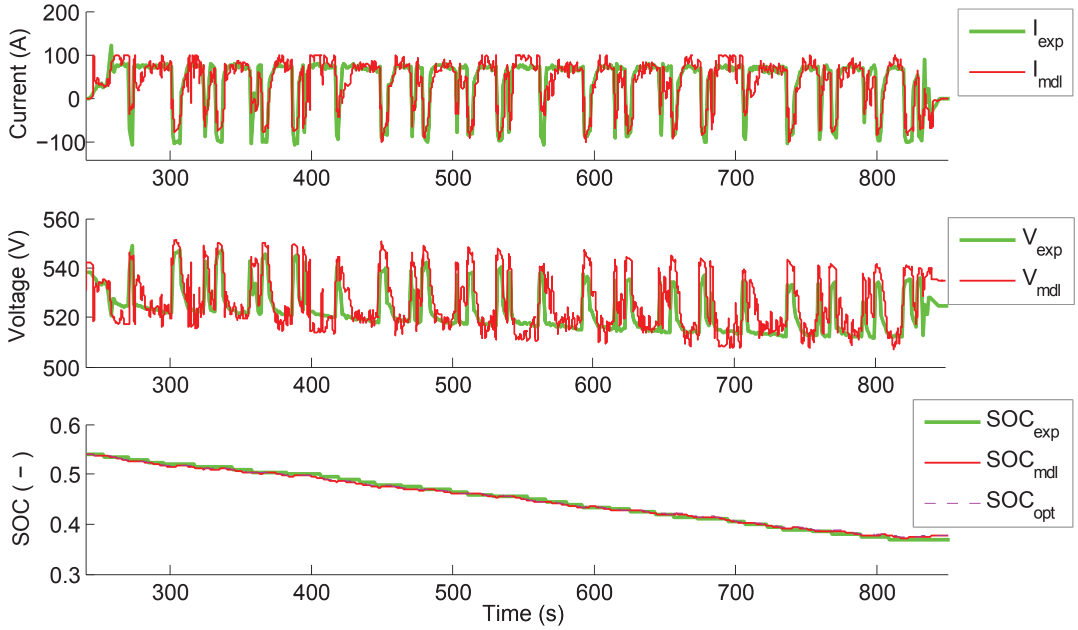


Figure 3.16: Results comparison of the current, voltage, and SOC evolution of the battery.

The fuel consumption is closely linked to the working points of the ICE, those working points are presented in Figure 3.18 which distribution are close to that from the experiment.

Analysis and Study for Improvements

In order to evaluate the choice of the working points, the brake specific fuel consumption (BSFC) and the optimal operating points (OOP) of the range extender combined efficiency are presented in the same plot. It can be seen that the main working points of the ICE are at nearly a constant rotational speed and variable torque, but not at the OOP line. This zone at speed of 470 rads^{-1} and torque ranged from 40 to 90 Nm is chosen for the actual control strategy because it coincides with the generator optimum operating zone.

According to published researches, the engine generator component of series HEV should be controlled to work at its best combined efficiency i.e. the OOP line to ensure a minimum fuel consumption. But, this also depends on the control strategy defined for this car; the engine is ON throughout this driving cycle and the battery outputs more power and depletes the SOC.

Since this rule based control method is proven to be effective to be used in a real time control, an operation with the same power produced at the generator but at optimal working points is studied. The results are presented in Figure 3.16 to show the same SOC evolution. Figure 3.17 shows the varying engine speed, the EG given power, and fuel consumption with and without choosing the OOP line. Distribution of ICE working points along the optimal line is shown in

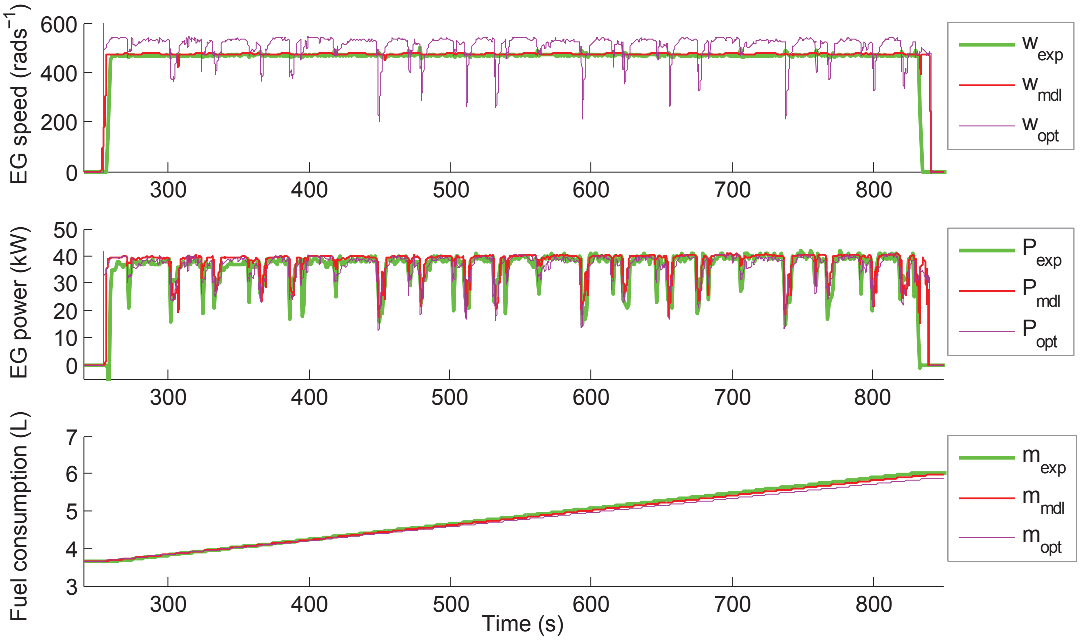


Figure 3.17: Results comparison of shaft rotational speed, given power at the generator, and integrated fuel consumption of the engine.

Figure 3.18.

In Figure 3.18, the concentration of the fuel consumption cannot be seen due to the superimposed operating points. So, it would be interesting to evaluate the fuel supply during start-up or transient operation of the engine and the totality of the working points to be able to assess its effect compared to its total fuel consumption.

The Figure 3.19 shows the tabulation in percentage of the fuel consumption for the actual control parameters. The most recurrent point is at the 80 to 90 Nm and between 400 and 500 rads^{-1}, with a fuel consumption of 1.368 kg, it represents 83% of the total 1.717 kg fuel used throughout this driving cycle. During regenerative braking, the EG output power is fixed at 30 kW and represents 13% of the fuel used, with working points situated at torque of 70 to 80 Nm and speed between 400 and 500 rads^{-1}.

Fuel consumption during start-up and transient is insignificant compared to its overall consumption for both cases. However in Figure 3.20, the most recurrent point shifts to speed between 500 and 600 rads^{-1} at 70 to 80 Nm torque with 78% of the total 1.652 kg fuel used. This consumption is 3.8% less compared to its original control. In same proportion, 13% of fuel is used during braking energy recovery, at the same speed range but it displaces its torque to a lower load at 60 to 70 Nm.

Through simulation, an improvement of 1% of the range extender efficiencies at the most re-

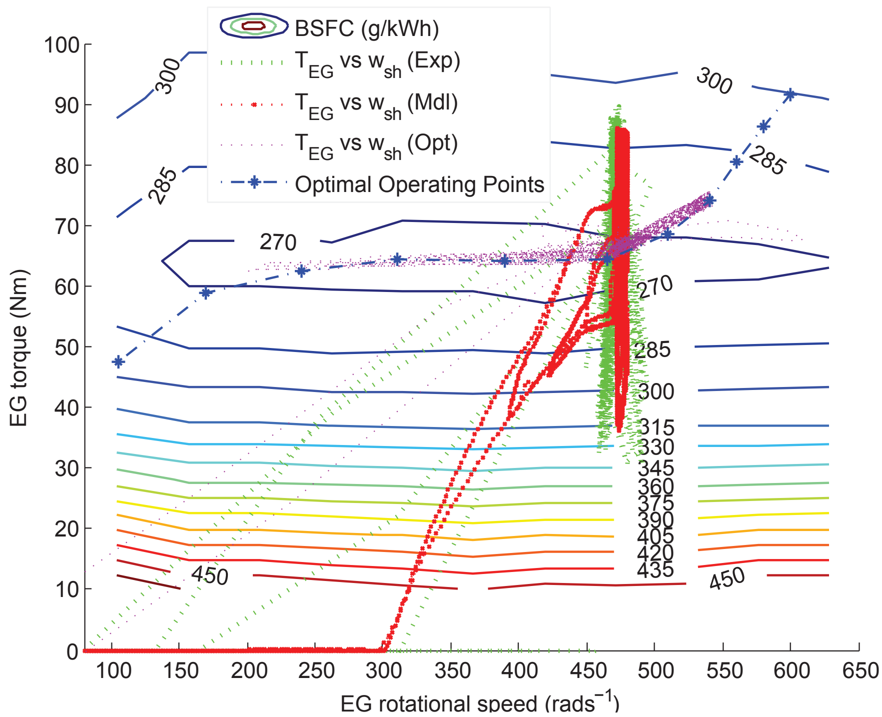


Figure 3.18: Engine operating points.

current points for both cases can reduce the fuel consumption by 26 g of each kilogram consumed for the actual control parameters and 25 g for the optimal control. More details of the results are presented in table 3.2.

Analysis on concentration of the fuel consumption on certain working points of the engine indicates location of the recurrent operation that will result the biggest impact after refinement. This approach can also be applied to species of pollutant emissions, by recognizing where the highest volumes occur and then to reduce it accordingly.

This analysis method will help engineers to focus the optimisation at a specific engine working points depending on the car utilisation. Moreover, in a hybrid system the engine operation is usually concentrated on a particular zone like the OOP line in the studied case regardless the type of the driving cycles. But this also depends on the control strategy and objective defined for a system, because different system architecture or sizing will have its own constraints to be respected. So, having a model that can show the system behavior close to the real system not only is advantageous for its development in terms of cost and time, but it also can be used as a tool to study and consider in advance any possible improvements of the system.

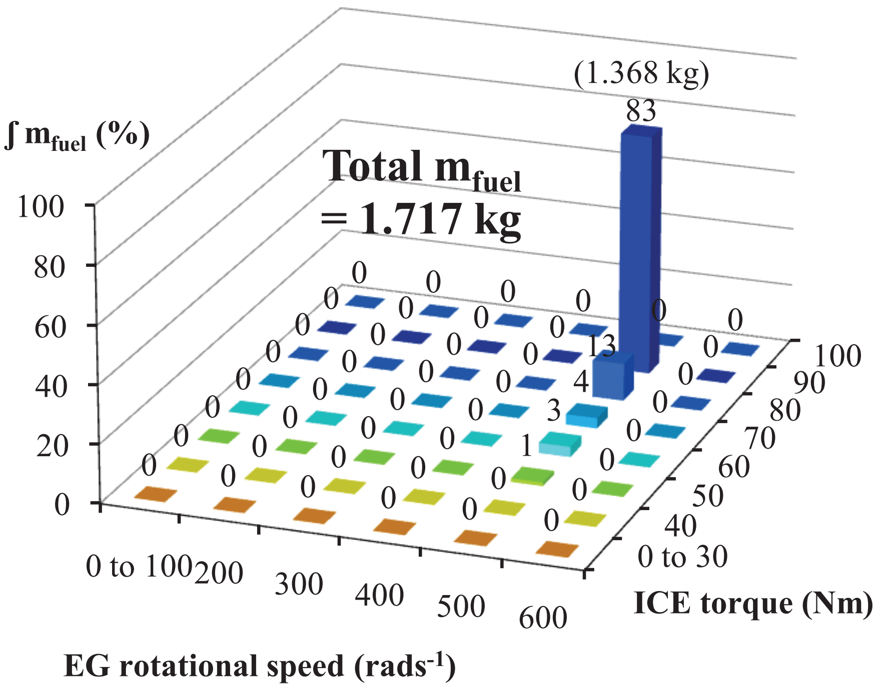


Figure 3.19: Percentage of the engine fuel consumption using the actual control parameters.

3.5 Study to Replace Component of the Range Extender by Fuel Cell

Environmental concerns has imposed a reduction of greenhouse gases emissions and energy consumption limitation to ensure a stable energy supply. This has led to a rapid development of alternative fuels and propulsion systems. Among all alternative drive systems, the fuel cell (FC) electric propulsion system has the highest potential to compete with the internal combustion engine [54, 53].

The fuel cell is one of the most promising converters able to use renewable energy. As it can use hydrogen from renewable sources, it can be considered as green power. Fuel cell systems have low emissions of nitrogen oxides and sulfur and at the same time they can operate with a very low noise level. In addition, they can provide energy in a controlled way with higher efficiency than a conventional power plant [120, 31].

Among the different existing technologies of fuel cells, the Proton Exchange Membrane (PEM) can be considered a good alternative for the use in electric or hybrid vehicles in which high specific power and rapid start-up at different temperatures have a significant importance [121, 122].

Recent development of fuel cell systems allows a significant reduction of weight and production price of the fuel cell stack and subsystems [123, 124]. Hybridization of fuel cells with battery

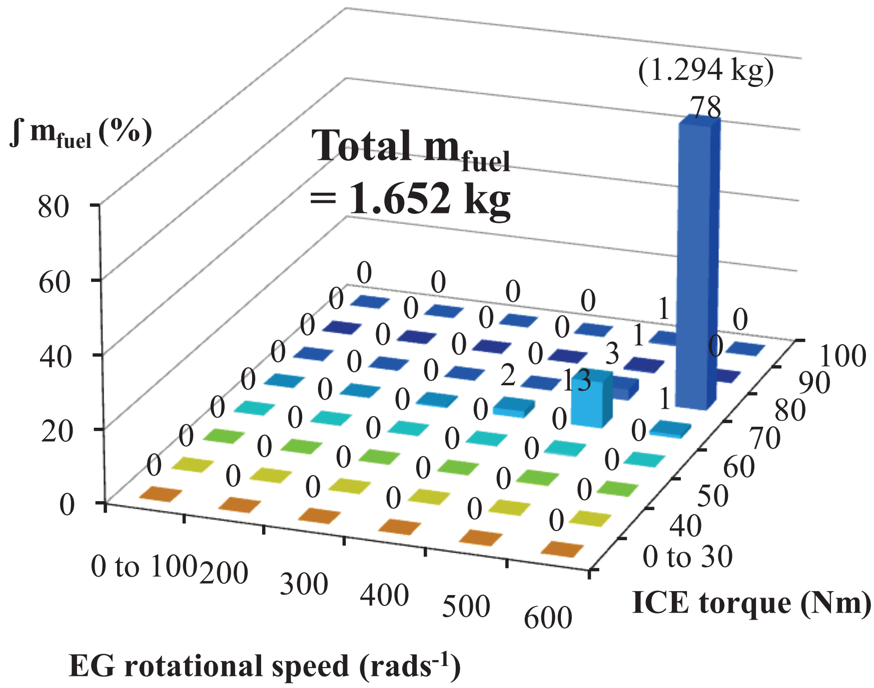


Figure 3.20: Percentage of the engine fuel consumption using the optimal control parameters.

or supercapacitors enables reduction of rated power of the stack and offers possibility to meet power demand with a smaller battery pack [122, 125, 126, 127, 128]. Moreover, it can avoid oxygen starvation and improve transient response due to a relatively slow dynamics of fuel cell stack [129].

A proper control strategy allows the fuel cell to have stable operation and the battery and or super capacitor to recover a maximum of energy from regenerative braking that can improve the hydrogen economy [126, 130, 131].

The application of fuel cell systems in a vehicle is especially attractive in sectors like freight and public transport because hydrogen storage place seems available and fuel cell system have a limited refuelling infrastructure [132, 133]. For a race car application, refuelling of hydrogen can be foreseen within the circuit infrastructure and there will be a room for the tanks in a single pilot vehicle.

This work presents the way of replacing the range extender with the engine and generator (EG) by a fuel cell range extender in the Noao racing car. The verified EMR model of this car original system becomes the reference to develop EMR model of the new architecture. In the first step, the same control strategy used in the original system are used to see the resulting operation using fuel cell for this type of application. Driving cycles deduced from drive tests of this car are used to analyse potentials of the fuel cell integration in this system.

Table 3.2: Improvement of the fuel consumption

Control parameters	Actual	Optimal
Fuel consumption (kg)	1.717	1.652
Recurrent point, Speed (rad s^{-1})	400 - 500	500 - 600
Recurrent point, Torque (Nm)	80 - 90	70 - 80
Fuel at recurrent point (kg)	1.368	1.294
Fuel at recurrent point (%)	83	78
Fuel reduction (g) if η_{ICE} +1%	45	41
Fuel reduction (%) if η_{ICE} +1%	2.6	2.5

3.5.1 EMR Model Development for the Fuel Cell

In the original system, it is equipped with a range extender consisting of a three cylinders direct-injection 1.0 L gasoline internal combustion engine (ICE) of 50 kW nominal power coupled to a 54 kW permanent magnet synchronous generator and the hybridization is reassured using a 23 Ah Lithium-ion battery pack. It uses the parameters presented in table 7.1.

The ICE based range extender will be replaced by a PEM fuel cell system in order to build a cleaner system and improve efficiency of the car. The vehicle original architecture is shown in Figure 7.3. The modified fuel cell/battery vehicle architecture is presented in Figure 3.21. Unlike the ICE/battery series hybrid system, which requires a permanent magnet synchronous generator to convert mechanical power from the ICE into electric power, the new design can deliver electric power directly to the power converter, thus reduces power losses due to power conversion.

As can be observed in Figure 7.6 and Figure 3.22, the traction part of this system are similar. But from the battery down to the secondary energy source i.e the charging part, the AC/DC rectifier will be replaced by a DC/DC converter and the fuel cell stack is simply taken as the charging source replacing the combined EG. The power supplied by the range extender is used to assist the propulsion or to recharge the battery.

Traction Part

The car environment becomes the mechanical source (MS) that yields the resistance forces F_{res} of the car. The force to accelerate the vehicle and the rotating parts inside the vehicle is equal to the available driving force F_d generated by the prime mover to overcome F_{res} (3.53).

$$M_v \frac{d}{dt} V = F_d - (F_a + F_r + F_g) \tag{3.53}$$

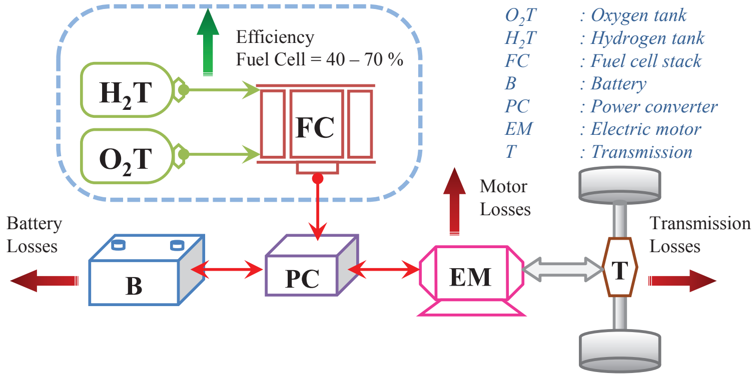


Figure 3.21: Architecture of the series hybrid vehicle system with fuel cell as range extender.

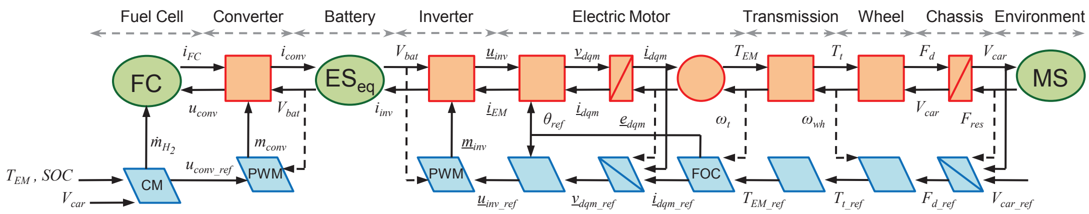


Figure 3.22: Energetic Macroscopic Representation and Inversion Based Control of the car system with fuel cell as the range extender.

$$M_v = m_v - m_{EG} + m_{FC} \tag{3.54}$$

Note that M_v is the total mass of the vehicle (3.54), and the fuel cell system weight m_{FC} depends on the selected maximum power of the fuel cell which will be used for the retrofit solution. The engine and generator weight, m_{EG} is directly proportional to its maximum power. The proportional factor is 2.0 kgkW^{-1} according to [134].

This model has been validated through experiments performed at the Nevers Magny Cours Grand Prix Racing Circuit as depicted in Figure 3.15 for the traction part. For this driving schedule MC1, the maximum velocity is 42 ms^{-1} for a maximum prime mover power of 82 kW.

Three driving cycles will be used in this study (Figure 3.23), the first driving cycle MC1 and the second driving cycle MC2 are conducted at the same Grand Prix circuit but with a higher given power for MC2. The third driving cycle, MCsp is a driving schedule obtained from drive test conducted at a smaller piste at this Magny Cours site.

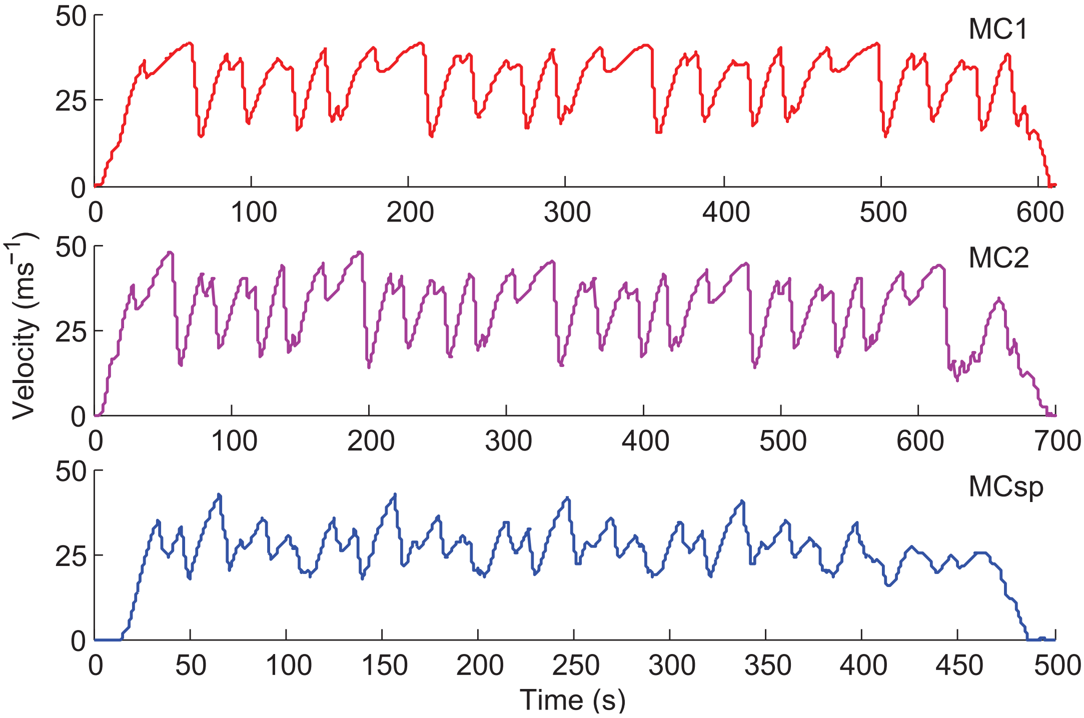


Figure 3.23: Driving cycles obtained from drive test of the racing car used for the case study; MC1, MC2, and MCsp.

Converter Model

In the original system, a three-phase full bridge controllable rectifier is used to adapt the output voltage to the bus voltage. In the new system, the fuel cell output is converted by a DC/DC power converter in order to supply FC energy to the DC bus. This power converter will have the same voltage level as the rectifier. The amplitude of the output will be in function of the input amplitude and modulation scalar m_{conv} (3.55) and (3.56).

$$u_{conv} = m_{conv} V_{bat} \tag{3.55}$$

$$i_{conv} = m_{conv} i_{FC} \tag{3.56}$$

Lithium-Ion Battery Model

The battery model is considered as an electrical source for the traction part and is assumed to be the equivalent electrical source (ESeq) to the charge part [110]. Thus, the battery current i_{bat} is considered as the total current entering or exiting the battery by inverter i_{inv} and converter i_{conv} (3.57).

$$i_{bat} = i_{inv} - i_{conv} \tag{3.57}$$

Fuel Cell Stack Model

For vehicle applications, the polymer electrolyte membrane (PEM) fuel cell, which operates at high temperatures, has proved the most attractive option [53, 122, 127, 126]. In this system, the membrane works both as a gas separator and electrolyte. This allows the hydrogen fuel side to react with the oxidizer (oxygen-air) in a controlled manner and to produce power at the electrodes, through the mediation of immobilized electro-catalysts bonded to the membrane.

This membrane-electrode assembly is referred to by the acronym MEA. Each MEA is interconnected via bipolar plate which performs several functions including gas distribution, heat dissipation and electrode current collection [126]. Furthermore, multiple single cells are connected in series to form stack assemblies with higher voltage outputs. Those stacks can provide a part of the energy needed by the vehicle through its controller.

The fuel cell chosen for the design is the proton exchange membrane (PEM) fuel cell that operates at 80°C [135]. As a design starting point, the fuel cell maximum power is set at 50 kW. In automobile application, the weight to power ratio of fuel cell system varies from 1 kgkW^{-1} [123] to 3.7 kgkW^{-1} [134]. Therefore, in this study the mass of the vehicle is kept the same as in the original system which means that in order to obtain a similar required power, the mass of the fuel cell stack is equal to the replaced EG assembly with a weight to power ratio of 2 kgkW^{-1}.

The fuel cell stack voltage V_{FC} (V) is obtained by (3.58). For a given type of cell, the resistance R_{fc} (Ω) is constant at a constant current operating conditions as well as specific pressure, temperature, and humidity. The variable V_0 (V) represents the open circuit voltage, or the voltage at which the linearized curve intersects the abscissa at i_{fc} (A), the normalized voltage at no-current state. The active surface per cell A_{fc} is 0.137 m^2. And the number of cells N_{cell} needed to form the fuel stack in series is 120 cells.

$$V_{FC} = N_{cell} V_{fc} = N_{cell}(V_0 - R_{fc} A_{fc} i_{FC}) \tag{3.58}$$

The nominal voltage of the fuel cell stack is 65 V at maximum power. This is shown in the polarisation curve in Figure 3.24. As a retrofit solution for the given application, the fuel cell replaces the EG and acts as power assist to help the battery to deliver propulsion power.

$$i_{FC} = \frac{\dot{m}_{H_2} 2F}{M_{H_2} N_{cell}} \tag{3.59}$$

Current i_{FC} (A) is deduced from the reference hydrogen mass $\dot{m}_{H_2}$ in kgs^{-1} calculated through charge management (CM) of the system (3.59), with M_{H_2} (kgmol^{-1}) is the hydrogen mass molar and F (Cmol^{-1}) the Faraday constant.

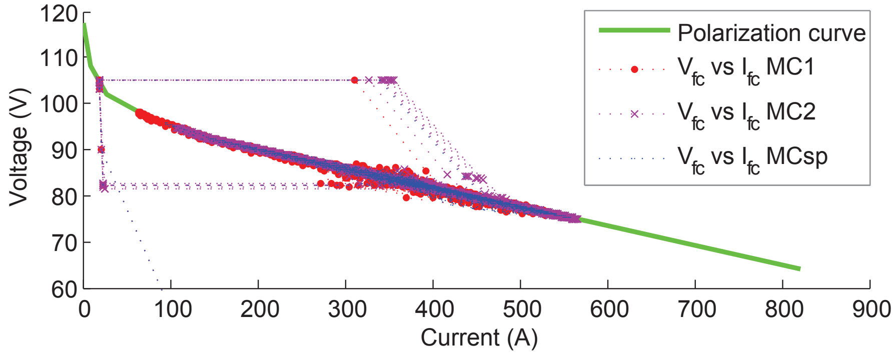


Figure 3.24: Polarization curve of the fuel cell stack and its operation points using the defined control strategy for the studied driving cycles.

3.5.2 Control Structure

Inversion Based Control

Using IBC method, each EMR elements of the tuning chain are inversed to deduce the control chain [110, 63]. The converter blocks can be simply inverted but a criterion input is required for inversion of the coupling devices [109]. Elements described by integral relationship such as the chassis, the electric motor accumulator, and the shaft require a controller C to invert them.

The continuous modulation functions m need measurement of the battery voltage V_{bat} (3.48), (3.60), and are converted to discrete variables using a pulse width modulation (PWM) in order to define commutation orders of the switches [117, 109].

$$m_{conv} = \frac{u_{conv\_ref}}{V_{bat}} \tag{3.60}$$

The inversion of the other components like transmission, wheel, and electric motor have been discussed before. The control of the wheel during braking depends on the regenerative braking system limits. The electric motor is controlled by field oriented control (FOC) method and needs measurement of the reference rotor position θ_{ref}.

Charge Management

In order to minimise activation loss and increase current limit for the same voltage the fuel cell is supposed to be heated to its operating temperature of 80°C before the start of each race [120, 136, 135]. At the same time, battery initial SOC is fixed at 0.9 and is expected to deplete to a final SOC of 0.3 after a number of laps by the end of a race.

Fuel cells have the best efficiency at partial load [136]. The aim of the control strategy is to distribute power so that the currents and voltages of the system operate within their safe limit and comply to the imposed race limits.

Due to its limited cycling capability, the fuel cell is less solicited during transient operations [54, 137] and during a race the fuel cell will be put preferentially in nominal condition to avoid start-up problems [133].

The charging part of the system considers the traction power needed at wheel and the estimated battery SOC as parameters to determine the reference recharging power for the range extender which rules are implemented via lookup tables. Like in its original system in Figure 7.6, the same parameter of T_{EM}, SOC, and V_{car} are taken as the input of the fuel cell charge management.

3.5.3 Results and Discussions

Results Analysis

The simulation results for the three driving cycles for the voltage of the fuel cell is shown in Figure 3.25 and its operation points distribution on the polarization curve is given in Figure 3.24. The fuel cell respected the voltage limits and operates mostly around 75 V for all three driving cycles.

The power generated in the fuel cell P_{FC} compared to the reference power P_{ref} and the FC output power P_{FCout} is presented in Figure 3.26 showing up to 76 kW P_{H2} for a 40 kW P_{FCout}. The fuel cell stack contains heat losses and losses due to compressor utilisation, thus causing a big difference between the generated power by the fuel cell and the power produced at the power converter.

The SOC evolutions are presented in Figure 3.27 with initial SOC of 0.54. SOC depletion MC1 EG belongs to the original system with EG. MC1 is about four laps of the Magny Cours racing circuit and is only a part of an entire race. For virtually the same expected SOC depletion for this racing car, the fuel cell hybrid can complete 26 laps, an extra of 10 laps compared to the original system with only 16 laps for a 72.20 km autonomy.

Comparison of results between the system with the engine and generator and the system with the fuel cell are documented in table 3.3. The MC2 has the highest velocity thus a highest energy consumption, while MCsp consumes the lowest energy. This is not only due to the duration of the driving schedule, but also because of the consumption rate (Figure 3.27) as revealed by the value of the final SOC.

$$\eta_{sysEG} = \frac{\int E_{drive}}{\int E_{bat} + m_f LHV_f} \tag{3.61}$$

$$\eta_{sysFC} = \frac{\int E_{drive}}{\int E_{bat} + m_{H_2} LHV_{H_2}} \tag{3.62}$$

Equations (3.61) and (3.62) are used to determine the efficiency of the system. The lower heating value of gasoline, LHV_f is assumed to be 44 MJkg^{-1} and 120 MJkg^{-1} for the LHV_{H_2}

Table 3.3: Vehicle system gain if hybridized with fuel cell

	MC1	MC2	MCsp
Maximum velocity (ms^{-1})	41.61	48.04	42.62
Mean velocity (ms^{-1})	30.08	30.90	26.13
Distance (km)	18.05	21.10	12.39
Driving energy (MJ)	24.36	32.11	16.16
Distance for 1 hour (km)	108.30	110.89	93.90
Engine and Generator			
Consumption battery (MJ)	10.43	14.80	4.79
Consumption fuel (kg)	1.71	1.93	1.31
System efficiency (-)	0.28	0.32	0.26
SOC final (-)	0.39	0.33	0.47
Autonomy if SOC 0.9 to 0.3 (km)	72.20	60.29	106.20
IMC (-)	38	34	39
Fuel Cell			
Consumption battery (MJ)	6.35	10.72	1.81
Consumption hydrogen (kg)	0.34	0.40	0.26
System efficiency (-)	0.52	0.55	0.49
SOC final (-)	0.45	0.35	0.51
Autonomy if SOC 0.9 to 0.3 (km)	120.33	64.92	247.80
IMC (-)	69	59	77

of hydrogen [136]. Consequently, the hybridization with fuel cell is proven to be more efficient. From simulation, the efficiencies of the EG based system are less than 32% whereas the efficiencies for the fuel cell based system are more than 49% depending on the driving cycles.

The system efficiency is better when the system uses more energy from the battery. However, this will cause a shorter autonomy for the intended SOC evolution from 0.9 to 0.3. And, the improvement of the driving range is less for the MC2 if the system range extender is changed to fuel cell.

Maybe, this is also because the defined control strategy is only optimised for the MC1 driving cycle, makes it suitable for this driving profile and less for the other driving cycles in terms of consumption, efficiency, and autonomy range. If possible, in some cases the control scheme is adapted to the type of a driving cycle or just on a specific driving cycle to ensure its optimal

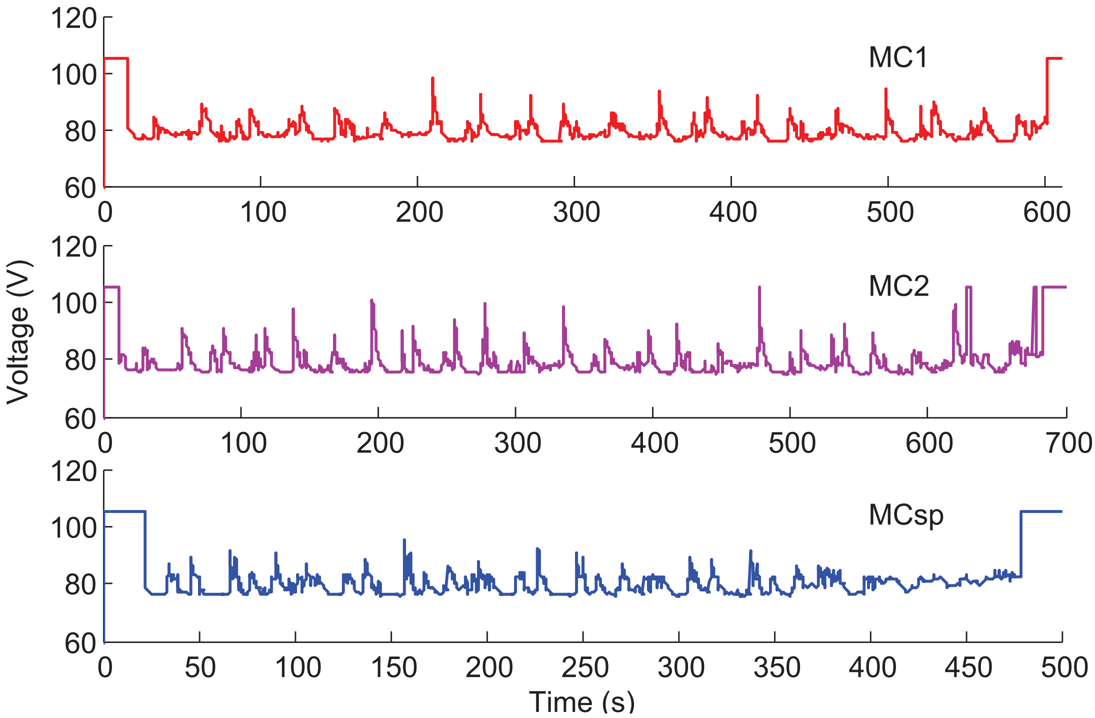


Figure 3.25: Voltage of the fuel cell stack in the racing car system for MC1, MC2, and MCsp driving cycles.

operation.

In the next section, improvements of the new architecture that will only concerns the MC1 cycle are further studied for a better integration of the new system.

3.5.4 System Improvements

Heure de Magny Cours

The Heure de Magny-Cours is a challenge open to all electric and hybrid vehicle with at least two seats. The challenge is to run the biggest possible distance during one hour at the Magny-Cours Grand Prix Racing track, a racing track with a length of 4411 m used for Formula 1 races. After the completion of the challenge, the Magny-Cours Index of the vehicle is calculated using (3.63).

$$IMC = \frac{V_m \cdot D}{y + z} \tag{3.63}$$

V_m is the mean velocity in ms^{-1}, with D the distance covered during the race in km, y the chemical energy consumed during the race in MJ, and z the electrical energy consumed

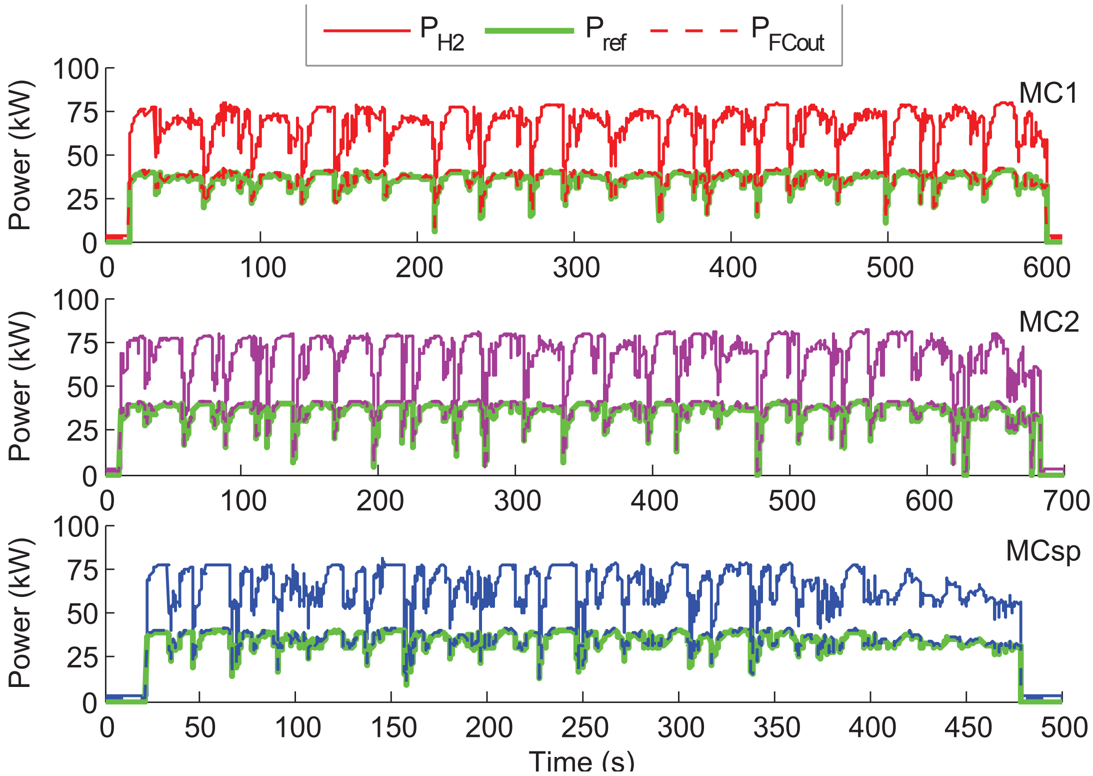


Figure 3.26: Comparison between the demanded reference power and the fuel cell power for MC1, MC2, and MCsp driving cycles.

during the race in MJ. The Noao in its original configuration would be able to obtain an (Indice Magny-Cours) IMC of 38.

Magny Cours Index

Based on the results of the simulation of the Noao with a fuel cell instead of the EG based range extender, considering the same MC1 driving performances, the car would be able to drive a distance of 26 laps. This new system reduces the SOC from 0.54 down to 0.45 and by using 0.34 kg hydrogen. This leads to a potential IMC of 69.

This is an increase of IMC of 31 points compared to the EG based solution, but it can be expected to have a further increase of IMC as the retrofit allows reducing weight and thus provides most probably a considerable gain in performance.

Weight Reduction

A fuel cell system with a 50 kW peak power for an automobile application is big, and its initial and operational cost will be expensive. Its supervisory control also will be very complex

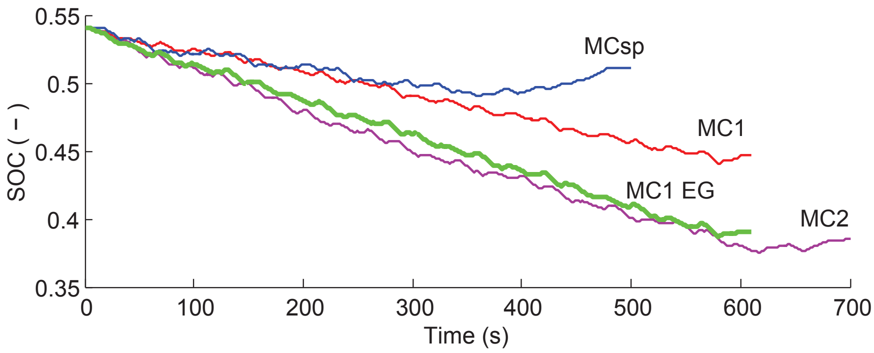


Figure 3.27: SOC evolution of the battery by using the fuel cell stack as range extender in the racing car system for MC1, MC2, and MCsp driving cycles.

Table 3.4: Study on the suitable fuel cell peak power

Peak power (kW)	50	45	40	35
FC stack mass (kg)	100	90	80	70
Number of cell (-)	120	108	96	84
System efficiency (-)	0.517	0.497	0.468	0.423
SOC final (-)	0.449	0.450	0.452	0.455
Autonomy if SOC 0.9 to 0.3 (km)	120	121	123	127

in order to put this system into the car. Since a FC system has a better efficiency, a peak power reduction that can lead to the weight reduction of this system is studied. This study concerns only the FC stack with the number of cells is reduced with regard to the resulting peak power.

The analysis is done by reducing the peak power from the preliminary power of 50 kW down to 35 kW. For each designs, the same reference race driving cycle MC1 and the same presented charge management are simulated.

The subcomponents size to form the fuel cell system package is considered identical. By referring to table 3.4, the system efficiency and final SOC will be higher in function of the increasing peak power. And since the control parameters are kept the same, there are no significant gain in the autonomy range for the reduced FC rated power.

In Figure 3.28, the peak power of the fuel cell stack down to 40 kW can be adapted for the given application. Then, the fuel cell voltage will be saturated and reach its limits under this value. An adaptation in the control parameters can push these limits to enable integration of a lower FC rated power, which is not studied in this study. Thus, for the moment in this study case a 40 kW fuel cell stack can be chosen to replace the EG based 50 kW range extender.

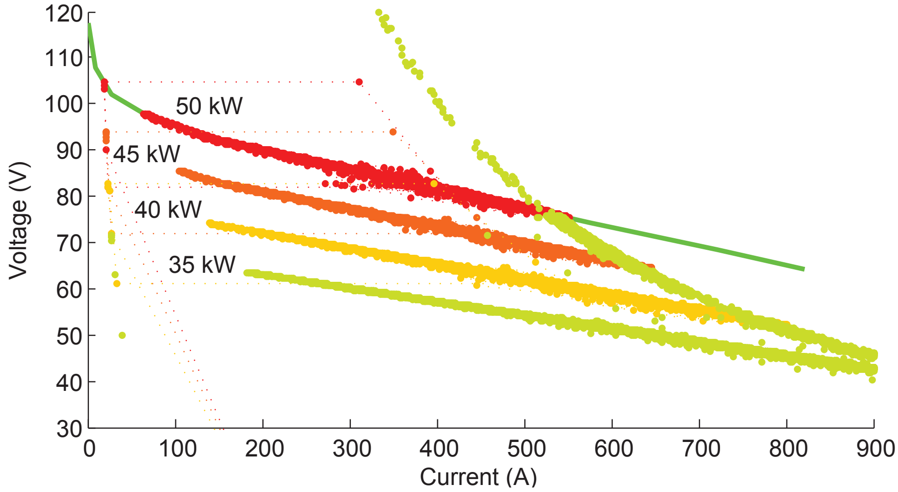


Figure 3.28: Operation points of the fuel cell stack using the same control strategy for the MC1 driving cycle.

3.6 Conclusion

A complete series hybrid racing car system is modeled using EMR and IBC. Comparison with simulation and experimental results shows that the system is correctly represented with regard to the electric traction motor, the battery system, the internal combustion engine and the electric generator, creating a valuable tool to further develop this system. Furthermore, the model can be used as baseline to develop a better control strategy for this system using a rule based approaches as well as optimisation approaches. Various improvements can be studied and effectuated by utilizing this method and model, like an optimisation of ICE working points to reduce consumption or hazardous emissions, an enhancement of the design parameters, or to design a better management system for the battery or the electrical machines.

This model is then used to further develop this system for a new architecture with a fuel cell stack at the charging part. Three race driving cycles are used to test potentials of the fuel cell integration. It can be concluded that with the same amount of requested power from the range extender, a hybrid fuel cell/battery race car is more efficient than the electric car hybridized using an EG based range extender. Due to its higher efficiency, fuel cell will provide a longer autonomy for the equivalent peak power of engine. The potential to improve the IMC from 38 to 69 that can be obtained by the vehicle due to better efficiency is shown. But, to avoid overdesign and to have a lower operational cost and weight, a fuel cell system with 40 kW rated power will fulfill the demands towards this specific racing car application. Even though the obtained results are not yet accurate, this model and approach to deduce the control scheme can be used at the first stage of component design and sizing of the fuel cell in the system.

A person who never made a mistake never tried anything new.

- Albert Einstein

There is only one way to avoid criticism: do nothing, say nothing, and be nothing.

- Aristotle

Chapter 4

Optimal Adaptive Control Strategy for a Racing Series Hybrid Car

4.1 Introduction

In the previous chapter, the vehicle system models are validated with the experiment results and some improvements can be effectuated to the car system to obtain a better efficiency. In this chapter, the optimizations will be focused on the control strategy to better manage energies available for the system.

The control strategy for HEV systems can be based on rule based method or optimization method. The rule based (RB) power management strategy is based on engineering intuition and simple analysis on component efficiency tables or charts [42, 138, 68]. It is robust and has less computational load [23, 15, 3, 4, 16]. The RB control strategy is easy to implement for a real-time supervisory control of power flow in a hybrid drive-train [8, 68, 23, 15, 4]. It can achieve near optimal solution, but cannot be easily implemented to another vehicle or driving cycle due to lack of formal optimization and generalization, thus may fail to fully exploit potentials of HEV architecture [23, 4, 7, 21].

The optimization based control methods can be local, global, real-time, parameter or threshold optimization. The optimization method can provide generality and reduce heavy tuning of control parameters [48]. Its task is to minimize a cost function in real-time or offline based on the vehicle and component parameters, as well as the performance expectations of the vehicle [21].

Real-time optimization method minimizes a cost function at each instant that depends only upon the system variables at the current time which have been developed using the system's past information. It has limits on knowledge of future driving conditions and the electrical path self-sustainability causing the solution to be not global optimal [48, 3, 21]. The common method is the equivalence consumption minimization strategy (ECMS) [68, 14, 9]. The ECMS is mostly utilized because it only relies on the equivalent factor (EF) to solve the optimization problem [9].

Global optimization approach can find a global optimum solution over a fixed driving cycle and known future driving conditions to determine power distribution of each system, it is unsuitable for a real-time vehicle control [48, 3, 139, 25]. It requires heavy computation and is usually used for offline simulation applications as a design tool to analyze, assess, and adjust other control strategies for online implementation [3, 14, 21]. The example of this method is Dynamic Programming (DP), Genetic Algorithm (GA), and Direct Algorithm.

In this work, DP optimization method is chosen to optimize the control strategy for this Noao car. This method has been widely utilized to optimize energy management of hybrid vehicles, and this time it will be used to optimize control strategy of a racing type vehicle system. The difference is the driving schedule, it is obtained from experiments carried out at the Magny-Cours racing circuit in France. A global optimization can be done because a precise specification of all components is available. DP is chosen over other approaches because it has established a reputation as the benchmark of other control strategies with its global optimum solution [8, 4, 4]. One of the interest of this study is to know how to implement this approach offline and then to adapt it for a real-time application in order to optimize the system power distribution using a predicted driving cycle.

4.2 Optimisation Using Dynamic Programming

DP can solve the optimal control of non-linear, time-variant, constrained, discrete time approximations of continuous-time dynamic models of HEV. It can achieve absolute optimal fuel consumption for different system configurations, but it needs all of the future conditions of inputs to be known a priori [139, 68].

DP is not implementable in real vehicle due to the preview nature and heavy computation requirement, therefore is difficult to be applied in real time control. But it can be used for offline simulations and to compare performance of a real time controller [8, 4, 26]. Stochastic DP has been implemented by Opila et al. [56] and Moura et al. [76] to be used in a real vehicle by selecting a finite number of sampled power demand defined using Markov-chain model.

The optimization of this car system has been included in our work to split power between the power sources using dynamic programming (DP) approach [140] and will be used to adjust control thresholds of the car.

4.2.1 Bellman's Principle of Optimality

In [141], Richard Bellman describes the Principle of Optimality: An optimal policy has the property that whatever the initial state and initial decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decisions.

Setting aside all future decisions, the first decision will be considered separately. The problem will be equivalent to (4.1), if the future decisions are in brackets on the right.

$$\max_{a_0}\left\{F(x_0,a_0)+\beta\left[\max_{\{a_t\}_{t=1}^{\infty}}\sum_{t=1}^{\infty}\beta^{t-1}F(x_t,a_t)\right]\right\} \tag{4.1}$$

Subjected to constraints (4.2):

$$a_0\in\Gamma(x_0), x_1=T(x_0,a_0), a_t\in\Gamma(x_t), x_{t+1}=T(x_t,a_t), \forall t\geq 1 \tag{4.2}$$

For the Bellman equation, the problem is taken as a recursive definition of the value function $V(x)$ (4.3). The optimal action $a(x)$ is obtained by finding the unknown value function of $V(x)$. V and a are in function of the state x.

$$V(x_0)=\max_{a_0}\{F(x_0,a_0)+\beta V(x_1)\} \tag{4.3}$$

It is subjected to constraints (4.4):

$$a_0\in\Gamma(x_0), x_1=T(x_0,a_0) \tag{4.4}$$

In order to solve the optimal control problem, the Bellman equation has been formulated for four cases: the discrete deterministic process, the discrete stochastic case, the infinite stochastic process, and the continuous deterministic process.

In HEV system, the optimal solution can be obtained for a known priori circumstances of a vehicle using DP. The solution is either used as a benchmark to compare an optimality of other control or as a reference to adjust an optimal control.

4.2.2 Analysis on the Actual Control Strategy

For this Noao car, the control target is to deplete the state of charge (SOC) of the battery from its high initial SOC at the start of the race and reach a low limit of final SOC after a number of laps at the end of a race.

A control method suitable for a plug-in HEV is a depletion of the battery charge from its higher limit to its lower limit throughout a driving cycle to achieve the best efficiency [4]. For a track competition car, the driving cycle will be the circuit driving schedule after a number of laps. The control strategy of this car consists of always putting the engine in mode to assist the car propulsion during races for longer autonomy.

From the previous chapter, as can be observed from the vehicle architecture in Figure 7.3, the generator transforms mechanical energy from the engine to electricity to recharge the battery or assist the motor for propulsion. The traction load torque only concerns electric motor torque, therefore the EG set can operate at its optimal working points at all times.

Also, the range extender controller has three subsystems to determine the rotational speed and the torque reference. Maybe, one subsystem can be added to the controller that will be a prediction component to determine the best thresholds for each type of driving cycle for this car system.

4.2.3 Dynamic Programming Problem Formulation

The objective of the optimization is to split power of both power sources in order to minimize the system power losses and improve energy efficiency through regenerative braking and power assist. The results are then utilized to adjust the control parameters to achieve the objective and improve the car endurance and enhance its performance.

The DP used for this car is based on the problem formulation discussed by Koot et al. [23], Brahma et al. [37], and Perez et al. [95] for a series HEV architecture. The power request at time t is the sum of both power sources (4.6), the power flow from the engine/generator and the power flow of the ESS. The ESS power is positive if the power flowing away from the ESS. The requested power here is defined as the amount of power needed at the electic motor.

Through optimization using quasi-static model formulated for this series hybrid car, the system is optimised to achieve minimum system losses, J (4.5).

$$J = \int_0^T \frac{P_{fuel}}{P_{EG}} dt + \int_0^T \frac{P_{bat}}{P_{ESS}} dt \tag{4.5}$$

The system optimization is subjected to its physical constraints, (4.6) to (4.8). The maximum power that can be delivered by the range extender is $P_{EG_{max}}$. $P_{ESS_{min}}$ is the limit of the power recuperation and $P_{ESS_{max}}$ is the maximum power limitation of the battery.

$$P_{EM}(t) = P_{ESS}(t) + P_{EG}(t) \tag{4.6}$$

$$0 \leq P_{EG}(t) \leq P_{EG_{max}} \quad \forall t \; \epsilon \; [0, T] \tag{4.7}$$

$$P_{ESS_{min}} \leq P_{EM}(t) - P_{EG}(t) \leq P_{ESS_{max}} \quad \forall t \; \epsilon \; [0, T] \tag{4.8}$$

The time-variant model takes battery SOC as its state variable x at each instance k and at power split ratio u. The initial state x_0 is the initial SOC and final SOC will be taken as the final state x_N.

The dynamic programming model is implemented in Matlab function developed by [89] and is modified to improve the power split factor, u_k applied for this system.

Battery SOC, x_k (4.9) (4.10) is the state variable at instance k, forms the time-variant model that includes the known variables of the driving cycle. N is the number of the time steps T_s, which defines L_N, the length of the problem (4.11).

Throughout this paper, the initial and final state variables x_0 and x_N will be changed according to optimizations carry out for this car.

$$x_{k+1} = f_k(x_k, u_k) + x_k \quad k = 0, 1, ..., N-1 \tag{4.9}$$

$$x_k \,\epsilon\, [x_0, x_N] \tag{4.10}$$

$$N = \frac{L_N}{T_s} + 1 \tag{4.11}$$

Optimization of the Actual Control

The rule based control strategy method implemented in the actual car decides the amount of power that will be delivered by the battery and generated by the EG set to assist the propulsion during traction and help recharging the battery during regenerative braking as can be observed in Figure 4.1. For this experiment, the SOC decreases from 0.54 to 0.37 after four laps of the circuit for the duration of 610 seconds. It chooses the operational points in function of the requested power to operate the EG around its optimal operating region.

DP optimization is carried out for the same driving cycle to see improvement that can be made on the system energy efficiency. It is because, it is possible for the EG to help recharging the battery or to be idle during regenerative braking phase. The compared values are presented in table 4.1.

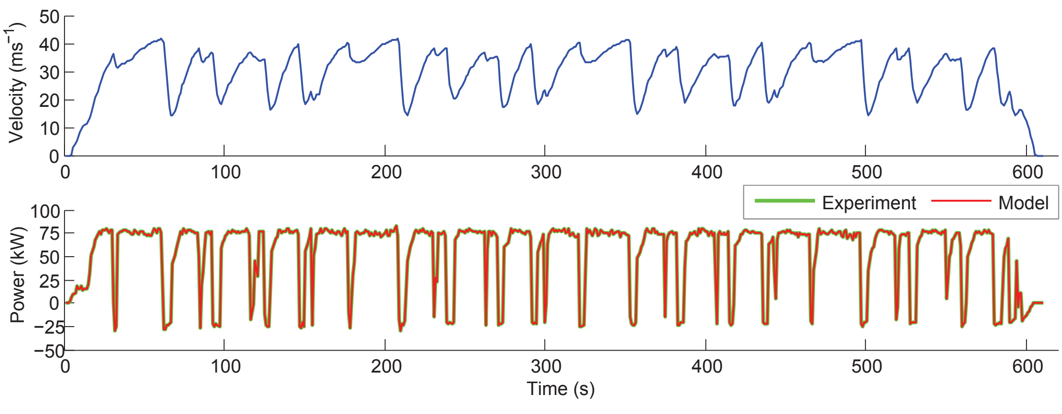


Figure 4.1: Magny Cours race driving cycle, MC1.

	Actual RB Method	DP	DP Endurance
SOC Initial	0.54	0.54	0.54
SOC Final	0.37	0.37	0.42
$\Sigma\ P_{req}$ (MJ)	32.448	32.448	32.448
$\Sigma\ P_{EG}$ (MJ)	20.894	20.513	22.790
$\Sigma\ P_{fuel}$ (MJ)	84.194	76.099	84.166
Average η_{EG} (-)	0.2482	0.2696	0.2708
$\Sigma\ m_{fuel}$ (kg)	1.914	1.729	1.913
$\Sigma\ P_{ESS}$ (MJ)	11.554	11.935	9.6577
$\Sigma\ P_{bat}$ (MJ)	11.599	11.769	9.6439
Average η_{ESS} (-)	0.9961	1.0141	1.0014
Average η_{system} (-)	0.3387	0.3693	0.3459

Table 4.1: Results comparison of DP optimization for the MC1 driving cycle.

Optimization to Obtain a Longer Endurance

As stated before, the battery charge is expected to decrease to its lower limit by the end of a target number of laps. And the existing defined control parameters can achieve 14 laps of the circuit with SOC depletion from 0.9 to 0.3, assuming the depletion is constant between this range.

The endurance of the car depends on the distance it can cover before the SOC falls to 0.3. Considering the same assumption, the car is imposed to complete 20 laps in this DP optimization to see its feasibility for a longer autonomy range. So, using the same driving cycle the state constraint which is the final SOC value is changed to 0.42.

Optimization for a Higher Performance

The same approach is used to enhance the performance of this car by using a more aggressive driving cycle for the same driving circuit. It is expected that it will have higher power consumption, rapid battery discharge, and cause more losses. But, the vehicle can arrive in a shorter time at the finish line which is essential for a racing car.

Experimental data obtained for this case study has higher limits of maximum power given by the power sources of the system. It results in superior velocity than the previous power configuration because it has more available power for acceleration as can be observed in Figure 4.2.

SOC depletes from 0.38 to 0.09 in 580 seconds to complete four laps of the circuit for this experiment, which means only eight circuit turns for the targeted 0.9 to 0.3 SOC diminution.

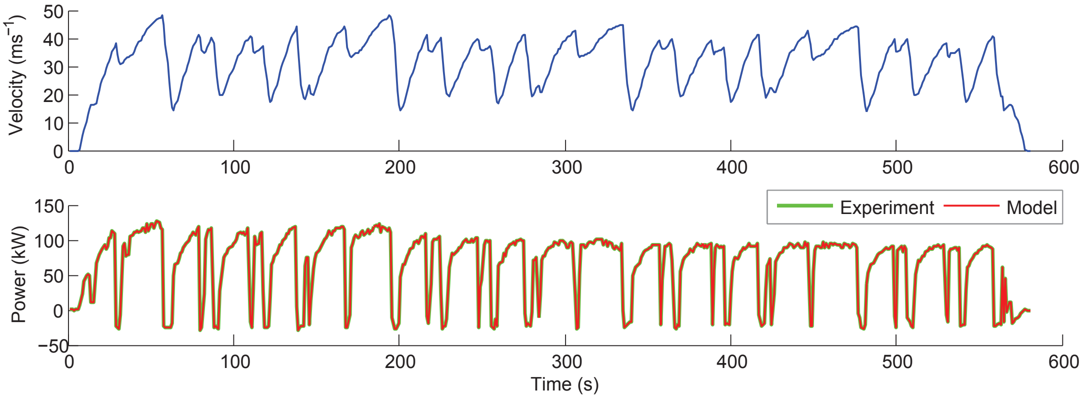


Figure 4.2: Magny Cours more aggressive race driving cycle, MC2.

After that, a higher SOC lower limit is set to see the maximum number of laps that can be achieved for this power configuration. The results of this case study are presented in table 4.2.

	Actual RB Method	DP Performance	Optimized Maximum
SOC Initial	0.38	0.38	0.38
SOC Final	0.09	0.09	0.14
$\Sigma\ P_{req}$ (MJ)	38.342	38.342	38.342
$\Sigma\ P_{EG}$ (MJ)	19.276	17.829	21.498
$\Sigma\ P_{fuel}$ (MJ)	72.600	66.483	79.377
Average η_{EG} (-)	0.2655	0.2682	0.2708
$\Sigma\ m_{fuel}$ (kg)	1.650	1.511	1.804
$\Sigma\ P_{ESS}$ (MJ)	19.136	20.514	16.845
$\Sigma\ P_{bat}$ (MJ)	19.063	19.354	16.073
Average η_{ESS} (-)	0.9962	1.0600	1.0480
Average η_{system} (-)	0.4183	0.4467	0.4017

Table 4.2: Results comparison of DP optimization for MC2, a more aggressive drving cycle of MC1.

4.2.4 Results and Discussions

Three study cases are highlighted in order to optimize the racing car system. As can be seen in table 4.1 and table 4.2, DP approach enables the system to have a lower fuel consumption and a better system efficiency compared to its actual utilized control parameters.

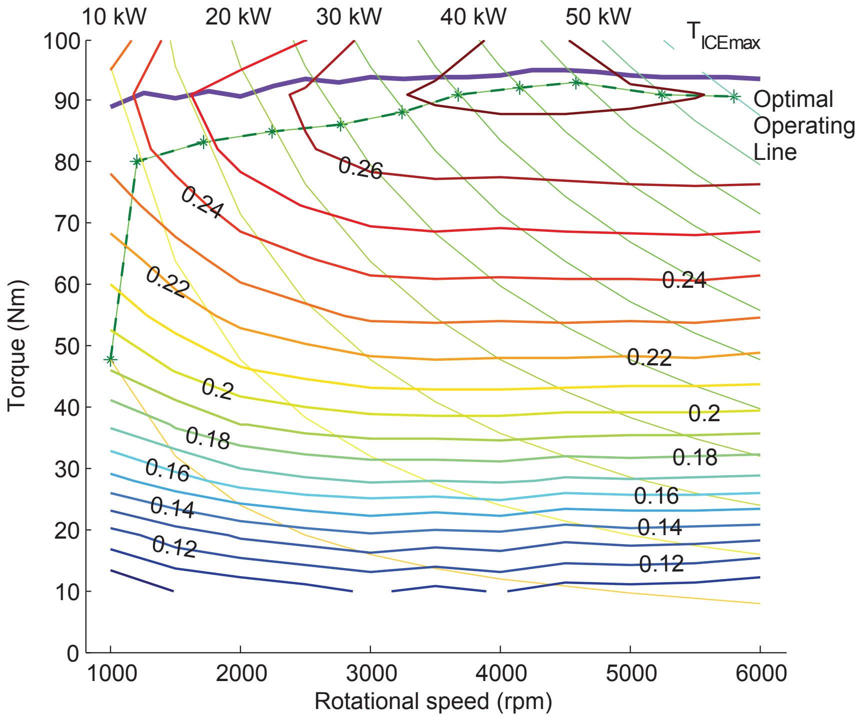


Figure 4.3: Optimal operating points on the combined engine and generator efficiency map.

Refinement of the actual system gives result as can be observed in Figure 4.4. For the same SOC trajectory, at the beginning of the driving cycle, DP optimization selects to use more power from EG, and then reduces its consumption to utilize more energy from the ESS to finish the rest of the cycle. As demonstrated in table 4.1, we can see that the optimization results in lower fuel consumption, enhanced fuel power efficiency, and improved system efficiency. Recuperated energy during regenerative braking has improve the ESS average efficiency which is simply taken as the total ESS power divided by the total battery power of the system.

The second study case is to improve the vehicle endurance. The results of both power profiles are presented in Figure 4.5 and the considered values are stated in table 4.1. As can be analyzed, the EG outputs more power to compensate battery energy utilization and choose to generate power during deceleration phase to help recharging the battery.

The Figure 4.8 shows the distribution points of the EG power in function of the power request compared between the actual RB control, DP optimization, and DP optimization for longer endurance. In the RB method, the points are concentrated at 40 kW EG power when the power request for traction is more than 60 kW. But for DP, the threshold is at 40 kW power request.

The EG power of RB goes to 0 kW when the power request is in the range of -20 kW to 20 kW, and then scattered between 15 kW to 35 kW EG power during regenerative braking.

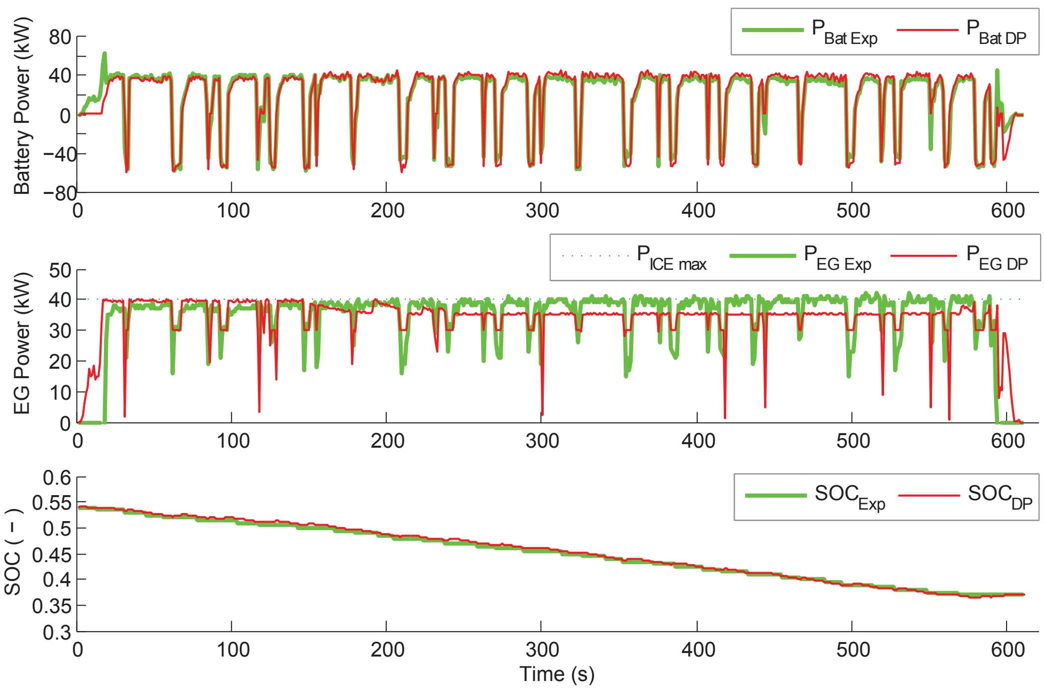


Figure 4.4: DP optimisation of the MC1 driving cycle.

However during this phase, DP chooses to help recharging the battery at 35 kW.

In this chart Figure 4.8, we cannot see the difference between the DP solution and the DP endurance, but we can study it further in Figure 4.4 and Figure 4.5. In the future these results will be used to recalibrate the control parameters of the electric generation path i.e EG power of the racing car for the regular (MC1) driving cycleof the circuit.

As shown in table 4.2, as expected in the last case study, the total power request is higher for this aggressive driving cycle than in its regular driving cycle. The car can arrive about 7.5 seconds earlier for each laps but it decreases the battery charge rapidly and causing important energy losses in the power train. In the real car, the system prefers to utilize energy from the battery to achieve a better performance.

Through optimization, DP method can improve the system overall efficiency during this condition. The fuel consumption is lower because it chooses to limit the EG power production as in Figure 4.6 to give a way for the battery to supply a slightly more power for propulsion for the same SOC trajectory like in the experiment.

In order to determine the maximum number of turns that can be completed by using this power configuration, the final SOC is set at 0.26. But, it turns out to be unattainable due to limitations and physical constraints of the system. And it gives 0.14 as the final SOC value demonstrated in Figure 4.7 which means a shorter autonomy range for the optimal SOC depletion.

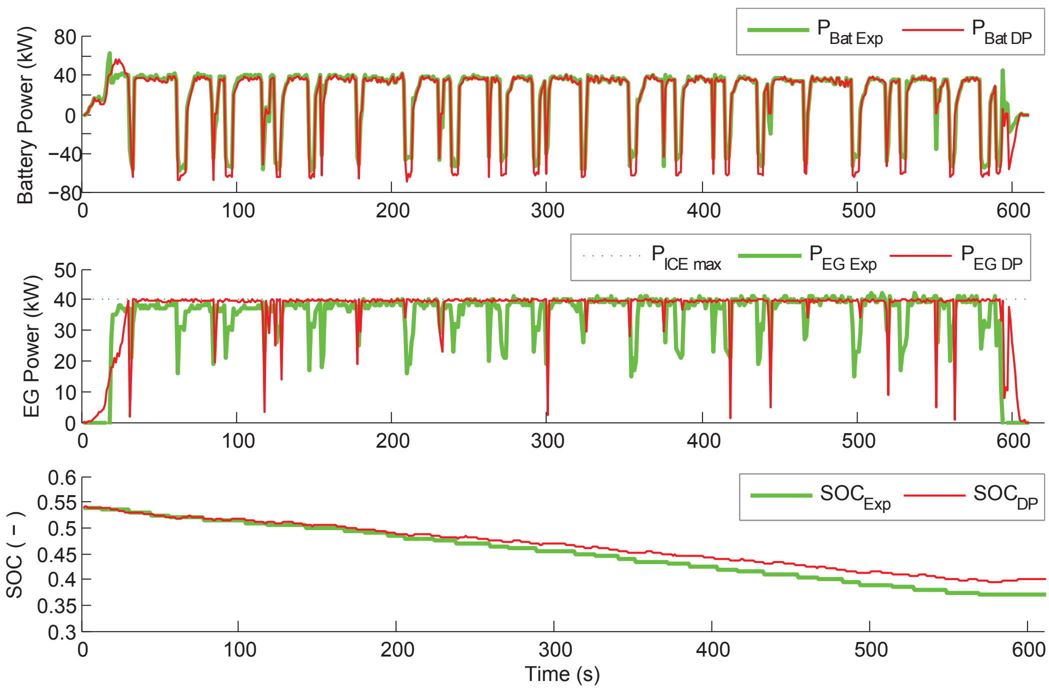


Figure 4.5: DP optimisation of the MC1 driving cycle for a longer autonomy.

This corresponds to only 10 laps of the circuit even if the EG tries to give a maximum power to recharge the battery during regenerative braking phase.

For the moment, even though this method is not applicable in the real vehicle, this approach can be the reference to set the parameters of the power sources to boost the performance of the vehicle optimally.

The simulations of the case studies are performed on a 32-bit Intel(R) Pentium Dual CPU 1.8 GHz with 2 GB RAM. The computational time for the calculation varies from 53 s to 65 s to analyse about 20 millions points, which mean 330000 potential points per seconds to solve these problems.

In the future, it is possible to consider the implementation of this method online by using the results obtained in this study. Because the driving cycle can be recognized in advance given the limitations determined for the power sources. The repeatable driving schedule during a race allows a segmentation of the optimization that can reduce the computational burden of the calculation. And the SOC trajectory is predictable through an offline optimization for the whole period of any race. The SOC evolution can be checked every time the car passes the starting point of the racing circuit and update its data for the next laps.

However, in this moment the DP for the online control of the actual control is still complicated to implement because of the computational burden of the DP. In the control unit, other inputs

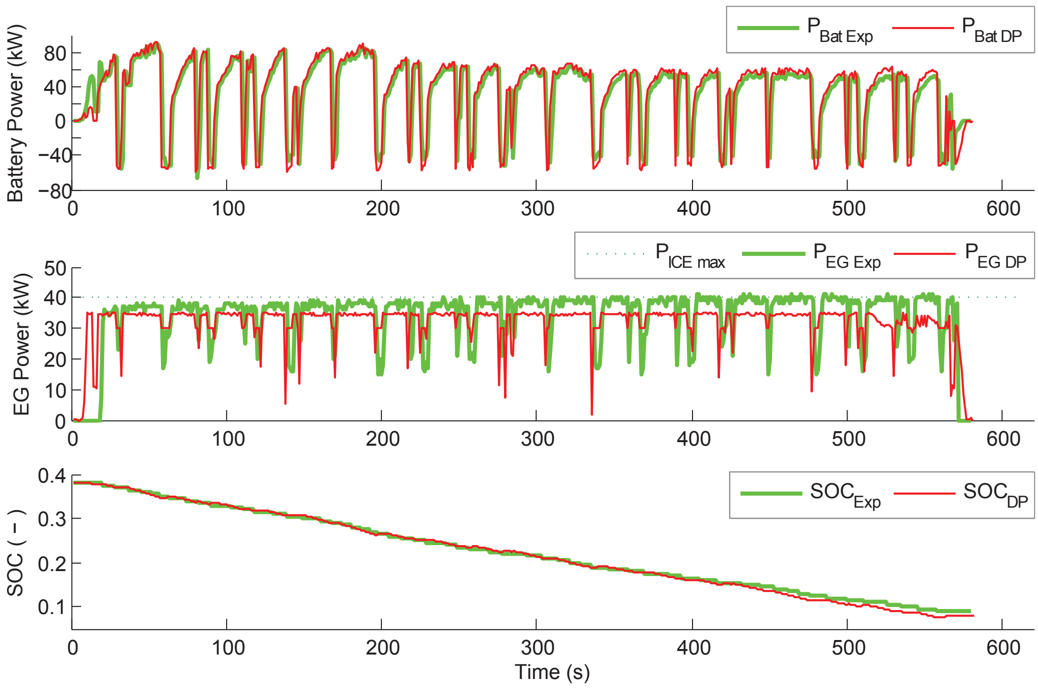


Figure 4.6: DP optimisation of the MC2, a more aggresive driving cycle of MC1.

from measurement are more critical to be supervised and need a fast time response. Even if the capacity of the computer is enough, DP deployment is still questionable in terms of the reliability of the obtained values and the rapidity of the calculation.

4.2.5 Endurance and Performance Limits

The feasibility study of DP optimization in function of number of laps is shown in Figure 4.9. It considers 0.9 as initial SOC and changes the target final SOC according to the number of laps to be completed for the optimal SOC depletion. As can be seen from the illustrations, the optimization for the normal driving cycle is feasible in the range of 6 to 18 laps and from 5 to 10 laps for the aggressive driving cycle. Below these ranges, it is better for the system to operate in electric only mode for better efficiency. The targeted battery discharge is unattainable above these ranges, except if the constraints are shifted.

On the range of optimal hybrid drive, the efficiency of the system decreases as the number of laps increases, and the fuel consumption increases in function of the distance. And it can be stated that more EG power will be needed to assist the propulsion to complete more laps, that causing the drop of overall efficiency for this system.

These limits will be used as reference to design an optimal adaptive control for this vehicle in function of the distance it has to cover.

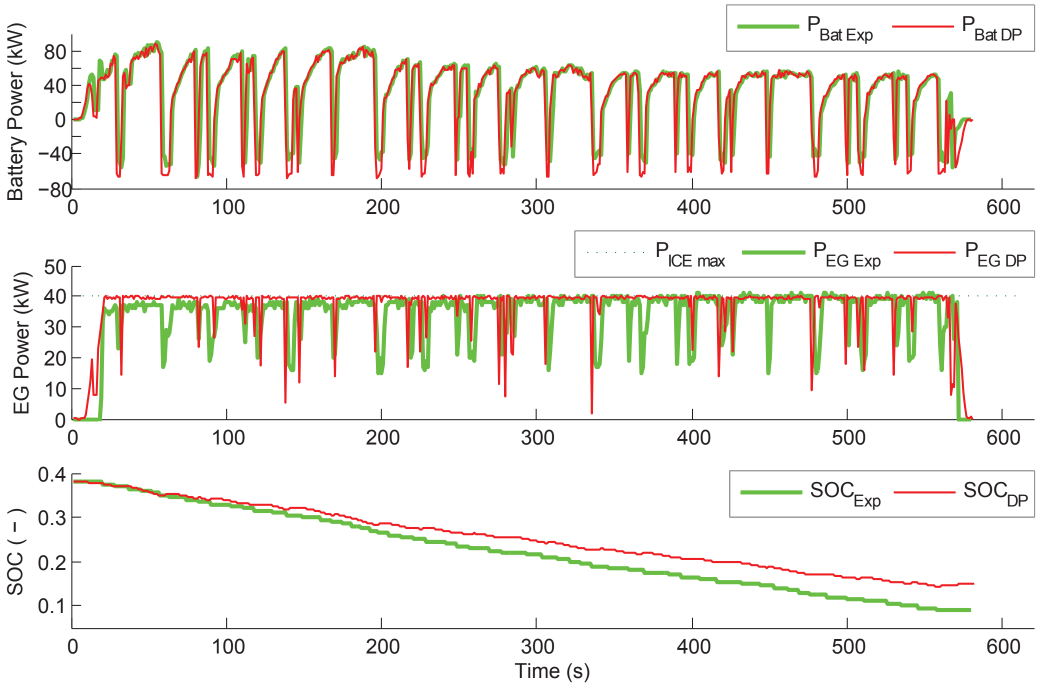


Figure 4.7: DP optimisation of the MC2, a more aggresive driving cycle of MC1 for a longer autonomy.

4.3 Racing Car Real-Time Adaptive Control

From this point on, the optimization and its study for real-time control will only concern the car operation of the first driving cycle on the Grand Prix racing circuit, MC1. The comparison between data from the experiment, DP optimization results, and the model with the modified control thresholds are presented in table 4.3 and in Figure 4.10.

In the actual car, a uniform EG power repartition is imposed along the battery SOC evolution with a slight augmentation in function of SOC depletion as described in Figure 4.10. About half of the power request is supplied by the EG with a threshold of 20 kW to 39 kW during braking and accelerating respectively. Through DP optimization, the EG power is chosen to be 40 kW maximum when the SOC is more than 0.5, and only 35 kW when the SOC drops under 0.5 with sometimes EG power is below 20 kW during braking in order to improve the system efficiency. This choice is probably caused by the resistance of the battery, different in function of SOC and different during recharge and discharge of the battery.

In table 4.3, average EG efficiency, η_{EG} is simply taken as total power delivered at electric motor by the range extender P_{EG} divided by total theoretical power produced by the fuel P_{fuel}, composed of the fuel indicated efficiency η_i, inefficiency due to engine friction, and the generator efficiency η_G. Same assumption is made to the average ESS efficiency, η_{ESS}, obtained by simply

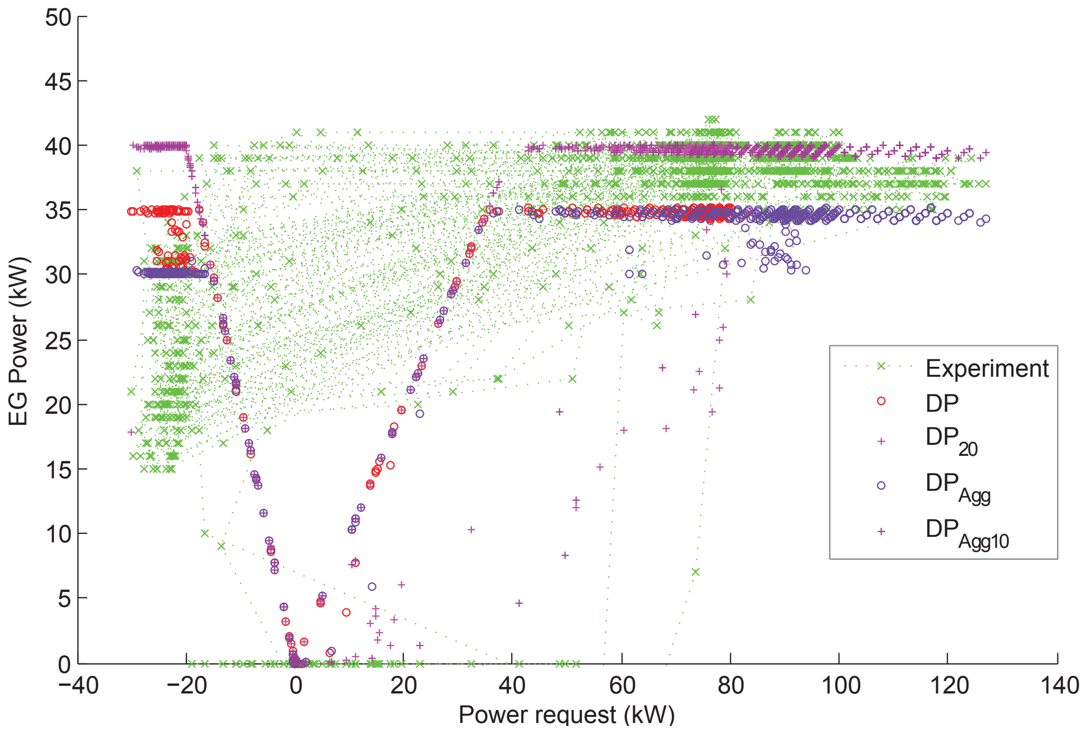


Figure 4.8: EG power in function of the power request.

calculating P_{ESS}/P_{bat}. ESS component is comprise of the battery and the power converter. This value becomes more than 1 because the battery absorbs the regenerative power and EG power during braking phase. For the system efficiency, it is calculated as the sum of powers to the electric motor divided by the sum of powers provided by battery, fuel, and regenerative braking.

4.3.1 Optimal Adaptive Method

Before applying the modification of the control threshold onto the real vehicle, the adjusted parameters are simulated in the model according to the results obtained by DP. Interpretation of the results and simplification have to be done in order to be able to implement the new parameters in function of the requested power and SOC. Therefore from observation of the requested power from regenerative braking to traction, if SOC is more than 0.5 the EG should deliver from 30 kW to 40 kW, and then 30 kW to 35 kW if SOC is less than 0.5.

By simulation using the interpreted DP results in the model, modification of the thresholds will cause a higher fuel consumption of 1.88 kg but a better system efficiency (0.3467) as can be observed in table 4.3. This is because more power from the EG will be delivered to the battery during regenerative braking, and SOC depletes slower to 0.4, whereas it was 0.37 before in the

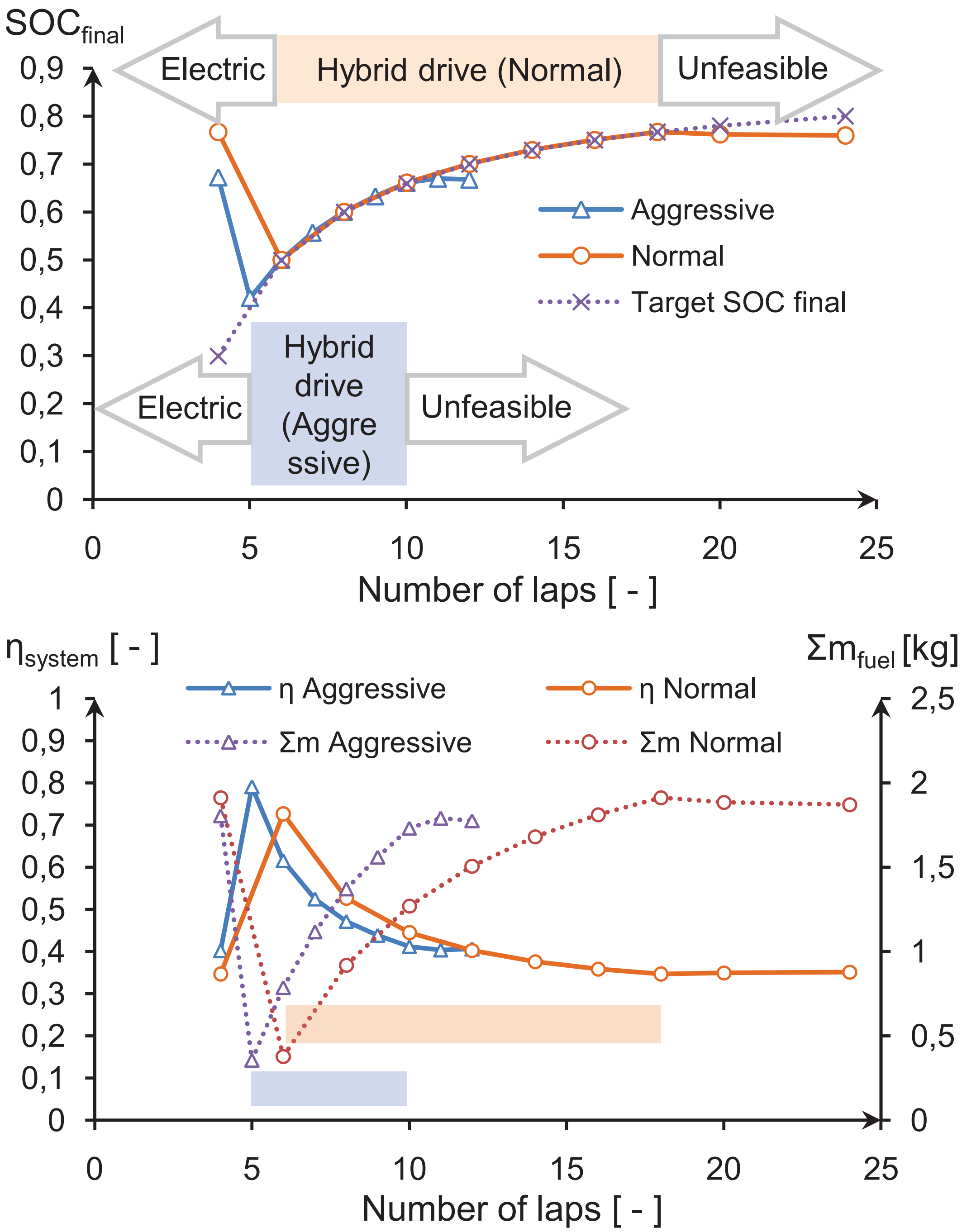


Figure 4.9: DP Optimisation limits for the two studied driving cycle.

existed control strategy. No specific pattern can be deduced from DP for the EG power when it is below 20 kW in function of the requested power or SOC.

The fuel consumption is lower, 1.88 kg compared to its actual control which consumes 1.914 kg, but less optimal than that one calculated using DP which is 1.729 kg. Nevertheless, the driving range of this car using the adjusted parameter will be longer for a targeted SOC drop from 0.9 to 0.3. Battery current comparison show nearly the same evolution for the three cases, all are within the currents limits defined for this battery.

This study shows how to optimise the system operation by interpreting results from DP for a fixed driving cycle with known future condition. Even if the exact future conditions are known, DP results cannot be directly applied for the real-time controller of the car to split power because a slight change of the car operation may cause the whole system to be not optimal.

In this study, the optimization is performed only on one driving cycle. It is expected that if it is to be applied on the smaller circuit with the same power limit, the system operation will be less efficient. The control strategy has to be tested on different driving cycles, and prediction method that will be discussed next will allow creation of a multitude driving schedules for different racing tracks and performances. Finally, the decision will be whether to use a specifically designed control strategy for a particular case or to design an optimal control for all driving cycles.

	Actual RB method	DP optimization	Adjusted parameters
SOC Initial	0.54	0.54	0.54
SOC Final	0.37	0.37	0.40
$\Sigma\ P_{EM}$ (MWs)	32.448	32.448	32.795
$\Sigma\ P_{EG}$ (MWs)	20.894	20.513	20.320
$\Sigma\ P_{fuel}$ (MWs)	84.194	76.099	82.710
$\Sigma\ m_{fuel}$ (kg)	1.914	1.729	1.880
Average η_{EG} (-)	0.2484	0.2696	0.2457
$\Sigma\ P_{ESS}$ (MWs)	11.554	11.935	12.475
$\Sigma\ P_{bat}$ (MWs)	11.599	11.769	11.889
Average η_{ESS} (-)	0.9961	1.0141	1.0493
Average η_{system} (-)	0.3387	0.3693	0.3467

Table 4.3: Results comparison of the three control strategies: Actual RB method, DP optimization, and the adjusted parameters for real-time control

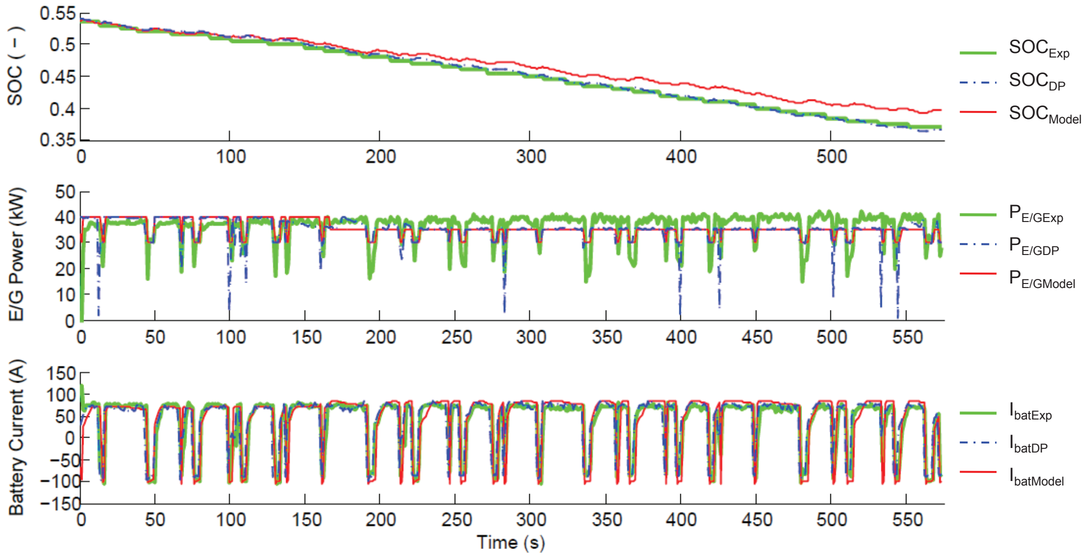


Figure 4.10: Comparison of SOC evolution and the systems power distribution for the experiment, optimization using DP, and the adjusted controller.

4.4 Driving Cycles Prediction

In a simulation, driving cycle play an important role in the optimization of a vehicle control algorithm. Besides of standard driving cycles, a multitude of driving cycles can be created using a cycle generator based on experiment data and statistics method [142], by developing a traffic flow model [4], adding the standard driving cycles with topographic profiles [68], or collecting the real world traffic data with onboard electronic equipments [143].

Eventhough the utilisation of driving profile known a priori does not represent a real driving situations, this non causal optimal solution can be used as benchmarks of the causal solution in development [35]. Studies prove that it is possible to integrate previewed elements as controller inputs via vehicle wireless technology [4], historical and on-line traffic information [23, 92, 4], or driving situation identifier [15, 77].

Identification of future obstacles such as heavy traffic, steep grade, and even power demand becomes easier using trip planning instruments like Geographical Information Systems (GIS) and on-board Global Positioning Systems (GPS) [18, 50, 82, 72, 28]. Approaches based on Model Predictive Control (MPC) can predict the future driving conditions efficiently for a sufficient long horizon [41], while a stochastic component of discrete time Markov chain can predict the future drive cycle by selecting a finite number of sampled power demand and vehicle speed [76, 56].

HEV system models have been developed for diverse applications covering topics such as optimal design problems [60, 40, 62], subsystems interactions [40, 53], controller development

[58, 50, 98, 23, 80, 17], and system drivability [56].

Even if the models that can represent accurately the series HEV system exist, a model development of this system that focuses on a competition car meant to generate its driving cycle is not yet available. A development of this car model depicted in Figure 4.11 to generate driving cycle using dynamic method is necessary to assess the performance of the car, and to evaluate its energy consumption and driving range during races.

The simulation has to include a module that emulates the behavior of the driver on pedal like in the real propulsion system [35]. Experimental data obtained from driving tests performed at Magny-Cours racing track are used to verify the accuracy of the model. Analysis of the track map and driving actions on certain zones of the circuit will be used to create a pattern of the driver behavior in function of distance.

This method will create a prediction tool to forecast inputs on car accelerator pedal position for other race tracks, obtain the driving schedule and to further determine energy consumption and battery state-of-charge (SOC) evolution of this car. As one of the objectives is to evaluate the distance the car can complete before the charge depletes to its lower limit. This will maintain the battery power capacity, prolong the battery lifetime and prevent the batteries from deteriorating dramatically due to deep discharge and high battery peak current [82, 17]. Moreover, without the need of car testing on the intended racing track, a database of racing driving schedules can be created using this method which are useful to optimise the system.

4.4.1 Driving Cycle Model Development Method

In the studied system, the actual control strategy defines battery current and EG power generation according to the command input from accelerator pedal as illustrated in Figure 4.11. The existing rule based control strategy is used to determine power repartition for the propulsion of the car.

During full throttle i.e maximum pedal angle, the algorithm will supply a predefined maximum power to wheels by compensating the drop of the battery charge with the power produced by the range extender. Operation of battery is controlled so that current operates within safe limits to prevent high battery peak current. This control strategy has been used to validate the simulation model.

As race application is different from other vehicles applications, this car needs a driving cycle database of its own for optimization purpose. This is because the existing standard driving cycles do not correspond to the design, and its driving style is not the same like any passenger car. This car has been tested on the real track of Magny-Cours Grand Prix racing circuit in Figure 4.12, and a smaller circuit at site in Figure 4.13. The driving test results are then analysed for further improvement of this car. A driving pattern is deducted by referring to the conducted experiment results and observation on drivers actions on pedal at particular locations of the

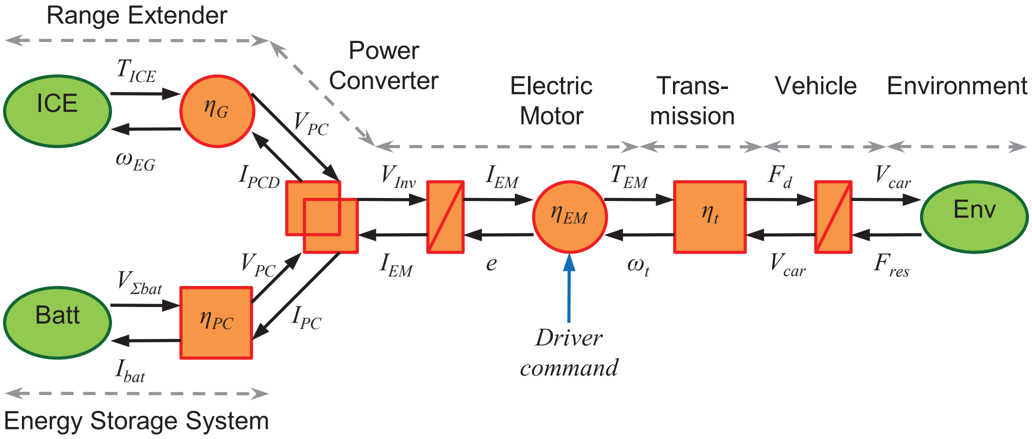


Figure 4.11: Energetic Macroscopic Representation of the car system to forecast driving cycles.

circuit. However, this driving cycle prediction method can only be realised if there is a good vehicle dynamic model of the studied system.

4.4.2 Magny Cours Circuits Map Analysis

The Grand Prix circuit is shown in Figure 4.12, it is 4411 m long and has eight cornering zones which can be distinguish in three categories; half turn, hairpin, and chicane. From the starting point, the zones are numbered from 1 to 8 with marks corresponding to the turning type. Zone 1 and 4 are the half turn, zone 2, 6, and 7 are the hairpin, and zone 3, 5, and 8 are the chicane. The characteristics of these zones are classified in table 4.4, but due to a tight corner of the turning zone 4, it is classified under the hairpin turning type because its turning angle is more than 90°.

Distance from starting point is the distance of the location where braking and accelerating actions are executed by the pilot and are marked in the circuit map. The apex point is the closest point to the inside of a corner and usually will be hit by the car when turning.

The map of the smaller club circuit is shown in Figure 4.13, also with eight cornering zones and a length of 2530 m. On this circuit, appears new category of cornering zone which is a combination of the half turn and the chicane at zone 1, 3, and 7. These zones have a form of the chicane, but with tighter angle and bigger gap between its apex points. Zone 2 and 5 are the hairpin type and zone 4, 6, and 8 are the half turn type which details are given in table 4.4.

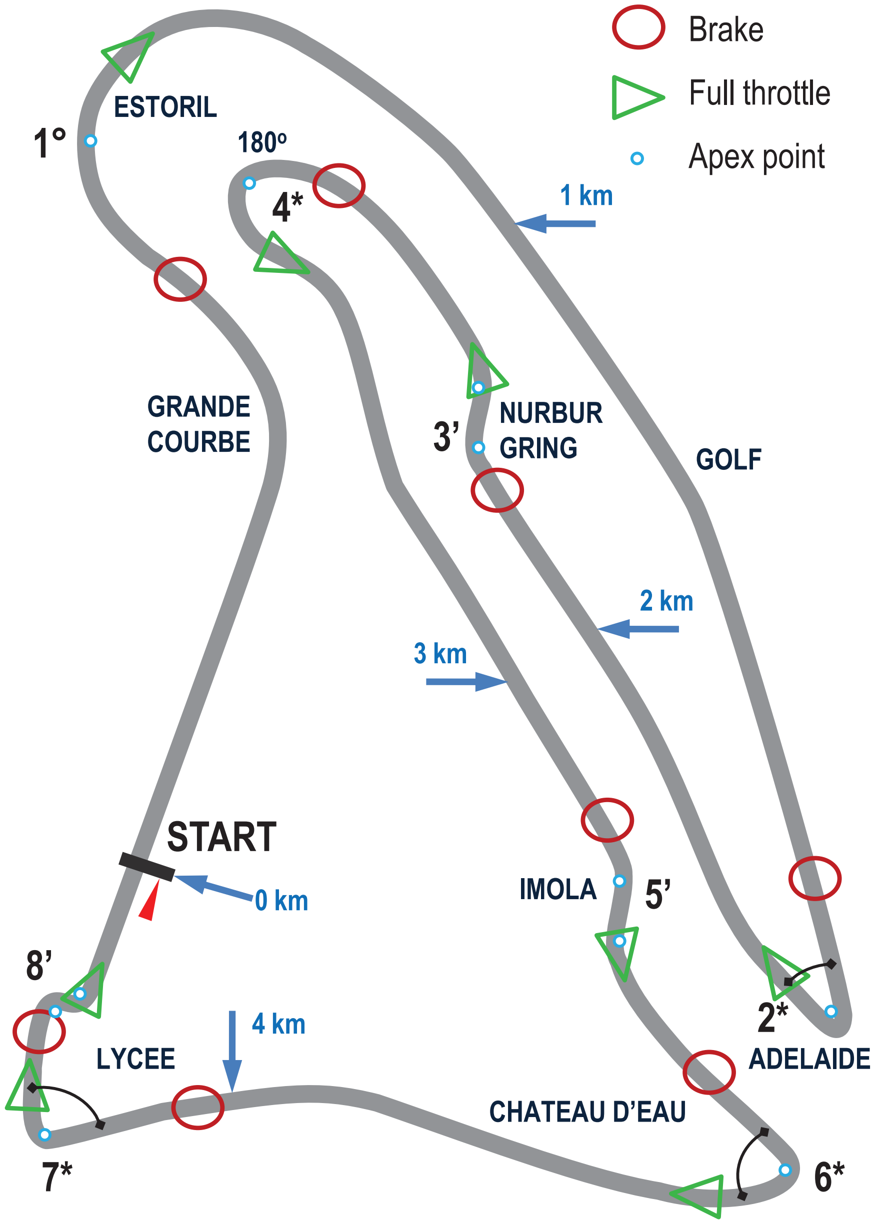


Figure 4.12: Map of the Magny-Cours main circuit with eight turning zones.

Grand Prix Circuit

	Distance from start $\pm$ 5 m		
Zone	Braking (m)	Full throttle (m)	Turn type
1^o	445	570	half turn
2^*	1850	1755	hairpin
$3'$	2190	2300	chicane
4^*	2490	2650	hairpin
$5'$	3160	3265	chicane
6^*	3460	3585	hairpin
7^*	4055	4205	hairpin
$8'$	4255	4315	chicane

Small Club Circuit

	Distance from start $\pm$ 5 m		
Zone	Braking (m)	Full throttle (m)	Turn type
$1^{o\prime}$	300	440	half turn chicane
2^*	615	715	hairpin
$3^{o\prime}$	1255	1395	half turn chicane
4^o	1530	1600	half turn
5^*	1910	2030	hairpin
6^o	2255	2335	half turn
$7^{o\prime}$	2370	2430	half turn chicane
8^o	2475	2515	half turn

Table 4.4: Magny-Cours circuits turning zones characteristics of the Grand Prix circuit and the Club circuit.

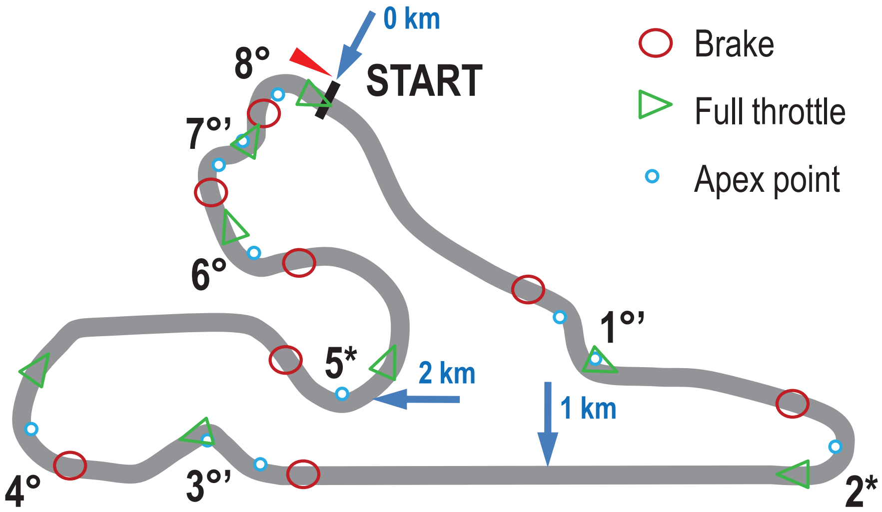


Figure 4.13: Map of the smaller Magny-Cours circuit with eight turning zones.

4.4.3 Drivers Action Analysis

Langari and Won [15] integrate a driving style identifier in the energy management agent and classify three types of driving styles; calm driving, normal driving, and aggressive driving based on average acceleration and its range specific standard deviation. In our case, driving style will be aggressive driving style. The driver behavior depends on many factors and cannot be defined with an exact mathematical model and it will not represent the real driving during competition races. But this information is useful for the construction of the driving cycle and the system maximum energy requirement.

The actions on the accelerator pedal are depicted in Figure 4.14 for the bigger circuit MC1 and in Figure 4.15 for the small circuit MCsp. The pedal acts on speed up and slow down of the car with a minimum angle of 0° to maximum throttle angle that is tuned at 83° in the first test and at 53° at the second test. Each braking action corresponds to a cornering zones of the circuit, we can observe that braking is brief and rapid (2 to 3 seconds) at the chicane turning zone. And the pedal is released more and longer (4 to 6 seconds) at the hairpin corners than the half turn corner (3 to 4 seconds). Braking action like in the half turn corner are doubled at the combined half turn chicane zone.

There are two apex points at the chicane zone, the car will brake until it arrives at the first apex, start stepping on the accelerator and reaches full throttle at the second apex. There is only one apex point at other cornering types which are specified by a long braking before entering the corner and the car starts to accelerate just after passing the apex point.

Analysis of the drivers behavior comprise only the pedal action; the analysis of the driver on

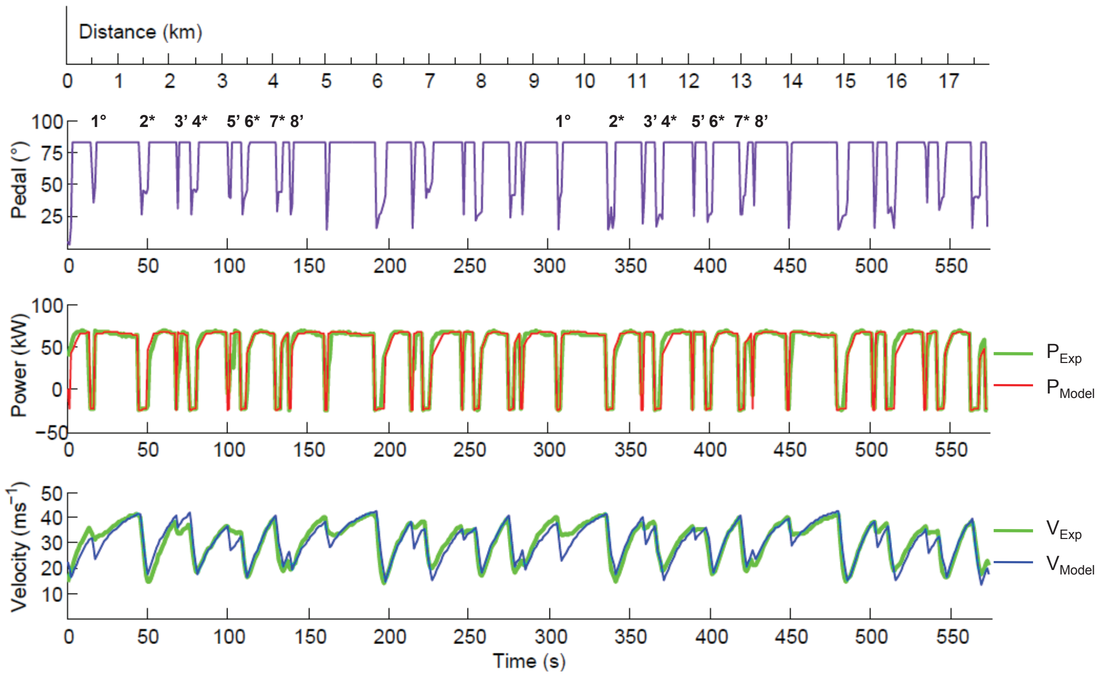


Figure 4.14: Comparison of the model with results from experiment for the Grand Prix circuit.

steering wheel is not included because the exact information of this element are not available from the experiments.

4.4.4 Results Comparison

The experimental results of this car are obtained through driving tests conducted on the Magny-Cours circuits. The test on the main circuit have been carried out for four laps of the track and 0.54 to 0.37 SOC depletion. The profile of power at wheels and car velocity are shown in Figure 4.14 and Figure 4.15 for the experiment and the model. The model is quite accurate and follows closely the experiment for the power profile but it is less precise for the speed profile with errors mostly at the cornering zones of the circuit.

This is because the vehicle dynamic model used in this paper is a single-wheel model and it does not take into account the effect of yaw angle when turning. That is why there are discrepancies in results of the velocity profile due to yaw motion, steering angle, skid effect, and tire lateral forces. However the tire longitudinal force is related particularly to power flow of the propulsive power, resulting a nearly same profile between the model and the experiment.

The power profile resembles the profile of the pedal with a maximum power of 70 kW at full throttle and a regenerative power of 25 kW when braking on the main circuit. Under this condition, the maximum velocity that can be attained by the car is 42 ms^{-1} (151.2 kmh^{-1}). The

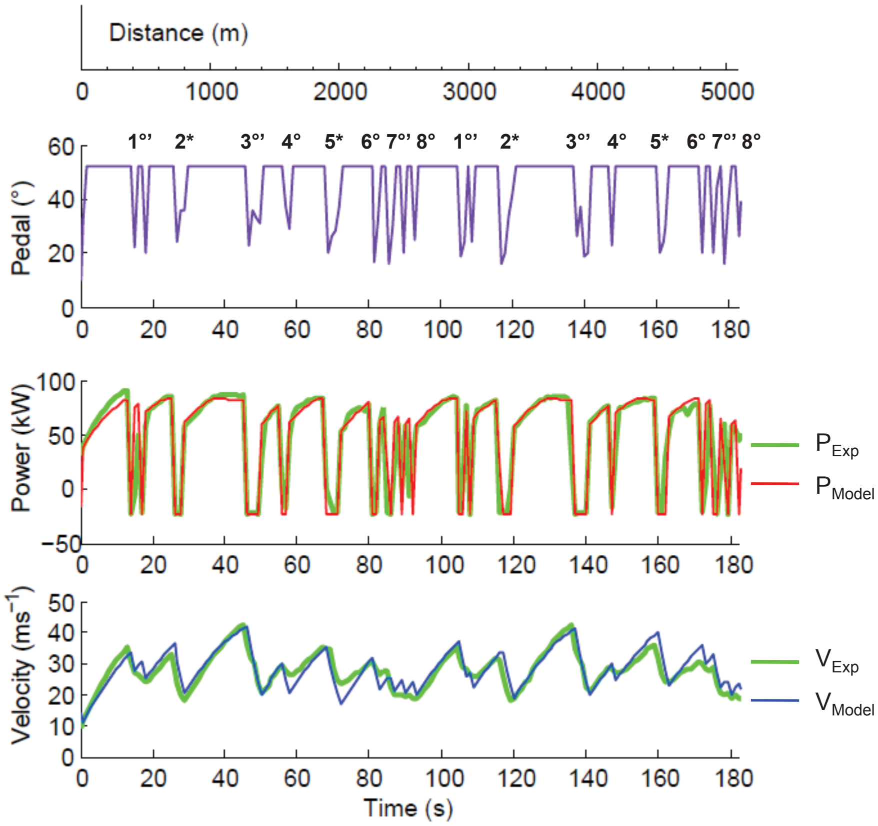


Figure 4.15: Comparison of the model with results from experiment for the small club circuit.

performance of a car depends largely on the available propulsion maximum power. It is expected that if the power limit is higher, the car will have more traction force as expressed in (3.53), resulting in a shorter drivetime and a higher mean velocity i.e better performance of the car but no longer the same driving cycle.

As can be observed in the results for the smaller circuit in Figure 4.15, the maximum power for this driving test is limited to 86 kW. Two laps of the circuit discharge the battery from SOC 0.37 to 0.3. As deceleration is limited by the tire adherence, the recuperation limit is the same for both cases. There are less occasions for long acceleration and this circuit is more difficult with its successives corners.

This car can reach a maximum speed of 42 ms^{-1} from 18 ms^{-1} in 17 s, faster than it can do at the bigger circuit which is from 30 ms^{-1} in 25 s. And a faster SOC diminution with a rate of 0.0138 per km on the club circuit compared to only 0.0096 per km for the Grand Prix circuit. At these rates, if battery SOC trajectory is limited to deplete from 0.9 to 0.3, the distance that can be completed at the small circuit will be only 43.5 km and 62.5 km on the Grand Prix racing track.

A compromise between its performance and driving range can be made by knowing the energy consumption rate of this car at a particular driving circuit, in order to prevent the battery from over discharged during races.

In this study, two racing tracks with different power limits have been analysed and simulated. And it can be concluded that for the different racing track, driver's pedal action on a particular zone type will be the same. In spite of the pedal maximum tuned value, the drivers aggresivity when pressing pedal will provide information of the power profile if simulated using a predefined maximum power.

The circuit map can provide information on the difficulty level of the circuit and the occasions this hybrid car will have for energy recuperation and acceleration. In order to obtain a new driving cycle, simulation and discretization have to be executed part by part according to braking and accelerating actions to match the drivetime with the distance completed.

As perspective, the precision of the generated driving schedules can be improved by using a more detailed models like single-track or two-track vehicle dynamics model. Utilisation of these models and analysis of a reference track and its curvature line can be used to predict steering angle that will taken by the driver. Nevertheless, the model used in this simulation using pedal as input can determine the maximum performance of the car, its drivetime, driving range, SOC depletion, and energy consumption that are useful to design a better energy management for the system.

The utilisation of this prediction method however will be limited offline, which means the optimisation should be done before the car uses the optimised parameters on an intended racing track. Or, the car can merge the results obtained from the prediction method and historical data from drive tests to further improve the parameters used during races.

4.5 Conclusion

A DP optimization method is applied on Noao series hybrid racing car with an ICE range extender. By using DP, the results from simulation show possible improvement in the fuel and system efficiency for the same driving cycle and SOC depletion from experimental result of the real car. The same approach of DP is used to study the possibility to increase the autonomy range of the racing car and proven to be feasible. These results are then analyzed and will be utilized to adjust the control parameters of the engine/generator power generation. Then, the DP approach is implemented to a more aggressive driving cycle applied for the same racing circuit. But the car has a shorter autonomy range under this condition. As perspectives, this global optimization approach will be studied further to be used in the racing car online control application. This approach can split power optimally only in certain driving range depending on driving cycles.

Then an EMR dynamic model is developed to forecast driving cycles of this series hybrid racing car system and to test the adaptation of the optimized thresholds for a real-time application. Single wheel vehicle dynamics model is utilised for simulation and it shows an acceptable accuracy with the race car real behaviour on the studied racing circuits. Comparison between actual rule based control strategy, DP optimization done for this car, and a developed model with adjusted control thresholds based on DP results shows an improvement on system efficiency compared to its actual power split control. For the same velocity profile and performance, the car with adjusted control can achieve longer autonomy over a targeted SOC depletion.

An analysis on pattern of pedal action on particular zones in function of its distance is presented for two different racing circuits and will be use as a prediction method to forecast drivers pedal actions on other racing tracks. This method is useful to obtain velocity profile and power profile of the car for determined power limits and create a multitude of driving cycles for its optimization in terms of fuel consumption, system efficiency, drivetime, or SOC trajectory. In the future, the model can also be used to redesign the parameters of the car components for a better performance or driving range. Outside racing car application, this method can be extended to predict driving cycles of busses or courier vehicles where the constraints will be similar; aggresive driving style, nearly fixed pathway, and a limited time to finish the circuit. The implementation will be different according to vehicle type, but the concepts of input utilisation will be the same in order to predict driving cycle and energy utilisation.

Measurement is the first step that leads to control and eventually to improvement. If you can't measure something, you can't understand it. If you can't understand it, you can't control it. If you can't control it, you can't improve it.

- H. James Harrington

Chapter 5

Engine Operational Points in HEV Applications

5.1 Introduction

In the previous chapter, the method consists of the development of the system model and its verification with the results from the experiment has been discussed. Through this chapter, this model is then utilised to simulate four control strategies that have been widely used for the system architecture which results will then be analysed for the ICE improvement as shown in Figure 7.7.

Published works discuss and propose a method to control hybrid vehicle system and evaluate its consumption, emissions, and implementation. In this chapter, the most utilised and proposed energy management methods that have been proved efficient and applicable for this system are tested through simulation and are further analysed. The analysis interprets the fuel consumption and time spent at specific points of the engine in terms of percentage because it is more representative for each driving cycles. Objectives of this analysis are:

- To identify the best and optimal control strategy suitable for this system and its application.
- To analyse the effect of different control strategy on the way of the energy sources consumed.
- To weigh the consumption at each operational points in the engine used for this system architecture.
- To determine the range of speed and load that can be optimised as measures to improve fuel economy for a hybrid system.
- To define the time spent on each working points in order to evaluate and reduce emissions of green house gases.
- To measure possible reductions that can be realized by improving particular working points of the engine.

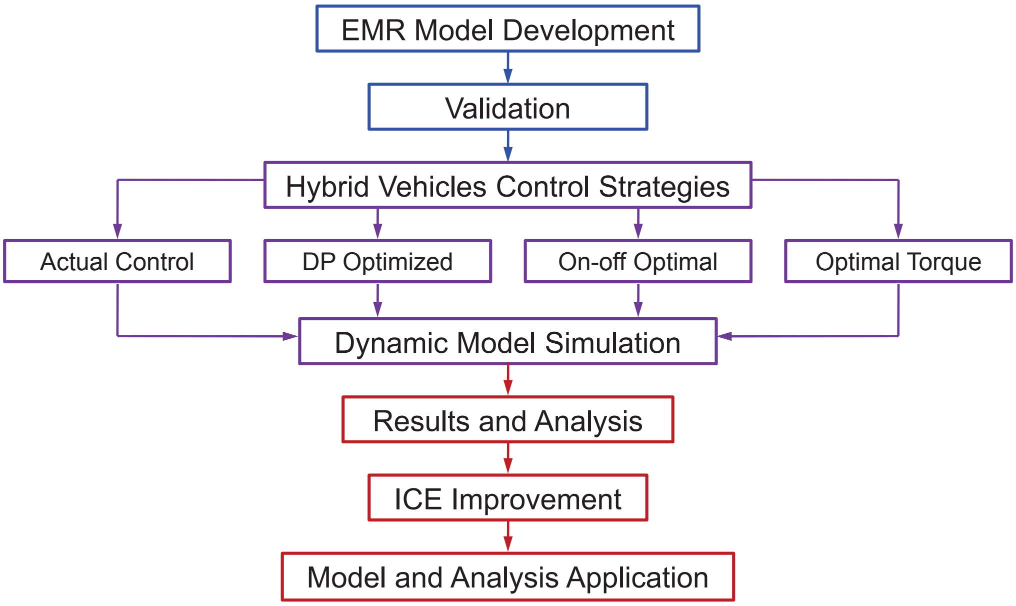


Figure 5.1: Process of the analysis.

This analysis method has not been conducted before because the development motive of this system is mostly focused on its optimal energy management. It is also time and ressources consuming for a real experimentation. By the time this model is developed there is still lack of a complete dynamic simulation model that can represent closely a real hybrid vehicle.

Replacement by full electric vehicle is long and still expensive for the whole transportation sectors. Instead of eliminating the use of engine, optimizing its utilisation can economise fuel and reduce emissions. One of the possible alternative is by identifying and measuring the most recurrent engine operation within this system that can give the biggest consequence after improvement.

5.2 Control Strategies

5.2.1 Actual Control Strategy

Tha actual control defined for this car imposes a constant rotational speed of engine generator (EG) when it is on. While the EG torque is varied according to torque request at wheel and weighted by SOC value to compensate battery voltage decrease. This control method is easy to implement and is based on engineering experiences. But it is not optimal because at the chosen speed the friction losses are high, however is advantageous at high load with minimum BSFC that make this control strategy suitable for racing cycles and not for road cycles.

5.2.2 DP Optimised Control Strategy

As discussed before, Dynamic Programming can be used as a tool to design an optimal control strategy. And with a recent development in telecommunication technology, DP can be used in real time over a predefined driving cycle. Known as a benchmark of other control strategies, DP is used to determine optimal energy distribution and its implementation is studied in the model.

Such programmation like DP can shorten the lengthy trial and error process to have a same initial and final SOC. In this control strategy, DP will choose an engine operation around the optimal operating points (OOP) line with minimum BSFC at each 5 kW power, shown in Figure 5.9.

It is assumed that the car is equipped with a sufficient capacity to calculate the optimal operation over fixed, known a priori, and did not change driving cycles which information can be obtained from historical or telecommunication data. Using these data, DP will output the profile of EG power that should be generated during the driving cycle.

This mean, each driving cycle will have its own different optimal generated power which will be optimal for the intended driving cycle, and will become less optimal if there are changes on the velocity or power request profile. It is expected that the battery charge will always depleted for the racing cycles because of the engine limited power.

5.2.3 On-Off Optimal Control Strategy

This control strategy is one of the most optimal control strategy [50, 55, 80] proposed for this vehicle architecture. Its objective is to have same initial and final SOC at the start and end of a driving cycle. Each driving cycle will have its own on time, calculated based on its energy consumption with an assumption that the car is equipped with predictive tools to calculate its total energy consumption which information can be obtained from a historical or telecommunication data.

Operation of the engine will be on one optimal operating point with minimum BSFC for the road cycles and it will be on at a portion of the driving cycle where power request is high. For the racing cycles, chosen initial and final SOC are like in DP solution and the engine is on whenever the system is working. The EG working points for race cycles will be beyond the minimum BFSC.

5.2.4 Optimal Torque Control Strategy

One of the optimal way to consume energy in a hybrid vehicle is by depleting the battery charge during the cycle and then reload the charge after the route is finish. And one of the most utilised control strategy in parallel and series-parallel architecture [81] is the optimal torque. Using this method, EG rotational speed will be the same as the speed transmitted at EM while the engine is imposed to generate an optimal torque at the rotational speed. The engine will be always ON and operates at the OOL.

This control strategy do not need information about the future driving cycles, but it will need a set of rules for recharging the battery if SOC reach its lower limit. The recharge will start after the cycle is finish at the most optimal point. Based on the vehicle parameters, there will be a good speed and torque accordance for the racing cycles, and less optimal for the road driving cycles because of the low rotational speed.

It has a good transient operation than other control strategies. The battery charge will deplete rapidly for the racing cycles that will shorten its autonomy. System efficiency can be improved by putting the engine off during low rotational speed. And a higher transmission ratio can shift the operational points to a higher value and better efficiency.

5.3 Results and Analysis

The analysis is conducted on two types of driving cycles; race cycle and road cycle. Three driving cycles considered for race type are obtained through drive test conducted at Magny-Cours Grand Prix circuit, the MCNoao1 and MCNoao2, and at a smaller piste at this site, the MCNoaosp. Velocity profile and its requested torque are depicted in Figure 5.2. MCNoao2 is a more aggressive driving cycle of the cycle MCNoao1.

Road driving cycles selected for this analysis are the New European Driving Cycle (NEDC), Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) for the rural roads [144], and the global harmonized of World Light Test Cycle (WLTC) class 1, 2, and 3 that have been developed recently. A special analysis will be presented for the WLTC3 cycle since the car used for this study is a high power vehicle with power to weight ratio (PWr) more than 34. ARTEMIS is the most aggressive driving cycles with frequent transient that consumes more fuel and energy for the road cycles.

Analysis of the results cover comparison of the fuel consumption and the SOC trajectory over different control methods implemented in this case study shown in table 5.1. The resulting operation of each driving cycles are presented in Figure 5.4, Figure 5.5, Figure 5.6, and Figure 5.7 showing the battery current, SOC evolution, given EG power, and the integrated fuel consumption.

The way of the energy consumed depends on objective of the control. The actual control strategy depletes SOC for the race cycles, but increases it for the road cycles suggesting this control mode is only suitable for competition purpose.

In DP, SOC depletes to a higher SOC than in the actual control strategy for race cycles, causing a higher fuel consumption in order to achieve same initial SOC at 0.54. But, it is unachievable due to a high energy consumption of the system and EG that has to assist the propulsion during these cycles cannot produce enough energy to recharge the battery. SOC

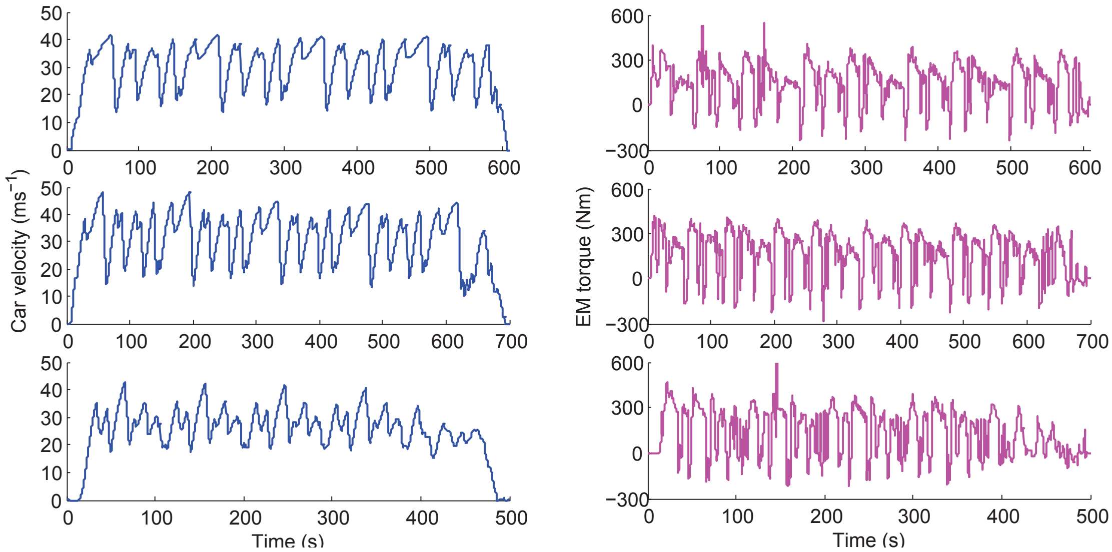


Figure 5.2: Race driving cycles (MCNoao1, MCNoao2, MCNoaosp) and its EM torque request.

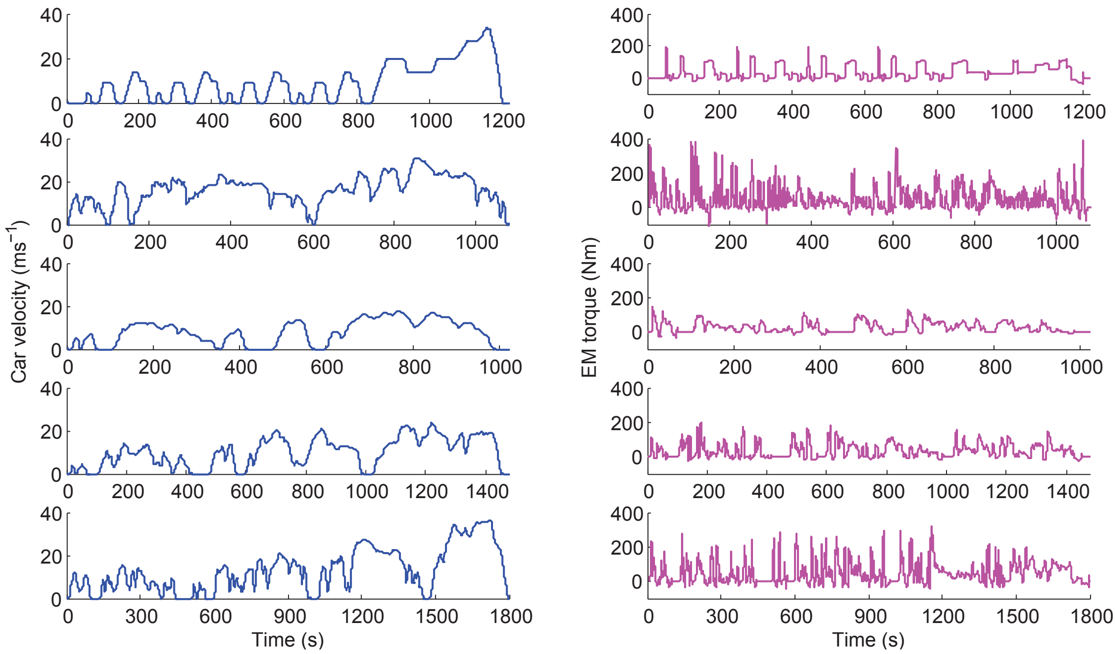


Figure 5.3: Road driving cycles (NEDC, ARTEMIS, WLTC1, WLTC2, WLTC3) and its EM torque request.

Table 5.1: Fuel consumption and SOC evolution of all cycles over different control strategies.

Cycle	Time (s)	Distance (km)	Fuel consumption m_{fuel} (kg) AC	DP	OP	WT	Final SOC (-) Initial SOC = 0.54 AC	DP	OP	WT
MCNoao1	610	18.05	1.710	1.782	1.755	0.801 (1.652)	0.39	0.42	0.42	0.29
MCNoao2	700	21.10	1.927	1.987	2.054	0.938 (1.651)	0.32	0.35	0.35	0.24
MCNoaosp	500	12.39	1.313	1.260	1.248	0.544 (1.071)	0.46	0.47	0.47	0.40
NEDC	1220	10.93	0.955	0.650	0.698	0.423 (0.679)	0.58	0.54	0.54	0.50
ARTEMIS	1082	17.27	2.011	1.109	1.135	0.708 (1.146)	0.66	0.54	0.54	0.47
WLTC1	1023	8.09	0.511	0.328	0.381	0.290 (0.355)	0.56	0.54	0.54	0.53
WLTC2	1478	14.66	1.355	0.737	0.796	0.558 (0.775)	0.62	0.54	0.54	0.51
WLTC3	1800	23.26	2.164	1.551	1.619	0.936 (1.643)	0.61	0.54	0.54	0.43
Total	8413	125.76	11.947	9.404	9.684	5.198 (8.972)				

increases then decreases to same initial SOC value at end of the road cycles. Its fuel consumption is lower than the actual control strategy, theoretically this amount corresponds to the minimum equivalent consumption to recharge the battery back to its initial charge.

On-off optimal controls final SOC to the same final value as in DP, resulting a slightly higher fuel consumption than in the DP solution for all driving cycles except for the cycle MCNoao1 and MCNoaosp. SOC decreases then increases to a same SOC value at the end of road cycles. In Figure 5.5, the constant EG power is about 37 kW during the system on period, and is 20 kW in Figure 5.7 for the road cycles with an on time that varied depending on the cycles.

SOC depletes faster in the optimal torque control strategy, to a lower final SOC than in the actual control strategy for the race cycles. Same case for the road cycles where SOC decreases to a lower SOC value at end of these cycles with a lowest fuel consumption than other control strategies. In table 5.1, the values in the bracket correspond to the total fuel consumption to reload the battery charge to the same final SOC as in DP which outcomes the lowest fuel consumption for the race cycles and the second best fuel consumption after DP for the road cycles.

The Figure 5.8 and Figure 5.9 show the distribution of working points on its respective map, BSFC for the engine load and the combined efficiency map for the given torque at EG. At these maps, the impact points are interpose each other for all studied control methods making the effect at each working points invincible. Usual practice is to mark them with colour tone [14, 25, 145]. A better perspective to view this result is to analyse the proportion at specific points by discretization and count them as presented in Figure 5.11, Figure 5.12, Figure 5.13, and Figure 5.14.

The distribution of fuel consumption on different regions of the engine and the integrated

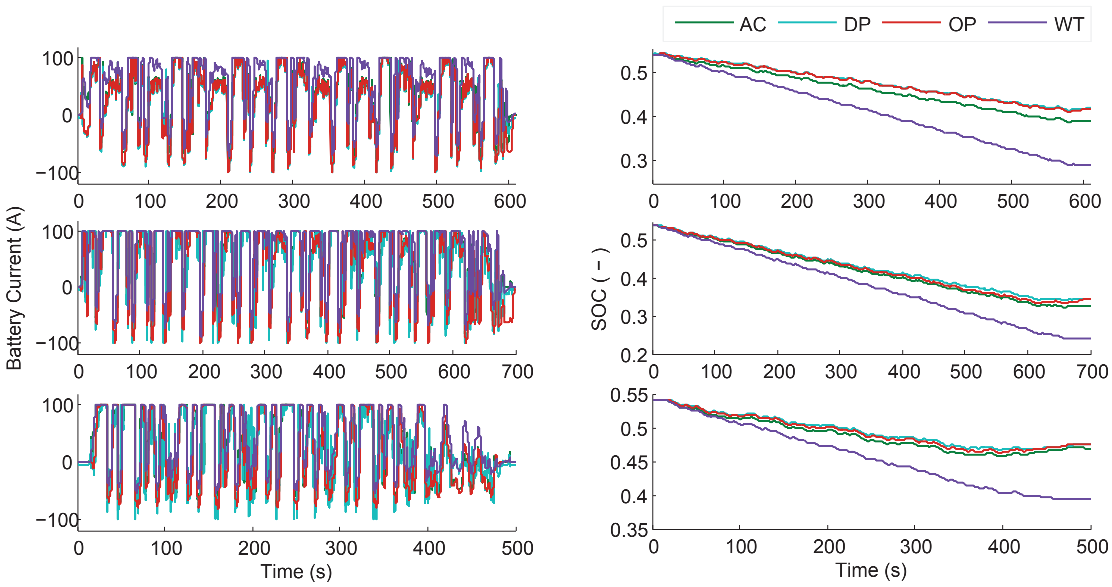


Figure 5.4: Results comparison of the battery current and SOC evolution of the race cycles (MCNoao1, MCNoao2, MCNoaosp) for all four control strategies.

instant past at these zones are presented in Figure 5.10 specifically for the WLTC3 cycle over all four control strategies, Figure 5.11, Figure 5.12, Figure 5.13, Figure 5.14 for the two types of driving cycle over each control strategies, and the overall analysis in Figure 5.15. The engine working points are divided into 48 parts, discretized for six portions of rotational speed, ranged from 0 to 600 rad/s, and eight load torque of 0 to 100 Nm with 0 to 30 Nm considered as one portion.

WLTC3 cycle is the latest driving cycle created for the whole world car test which best represent the power rate for this car. 89 % of fuel will be consumed at 400 to 500 rads^{-1} speed, 70 to 90 Nm torque load if using the actual control with only 37 % time spent. By using DP, the most fuel used zone is at 200 to 400 rads^{-1} speed, and at 60 to 70 Nm with 45 % of time is spent here. Only one point will be used for the on-off optimal point control strategy, which is at 300 to 400 rads^{-1} speed and 60 to 70 Nm torque with 60 % spent time at this point. But for the optimal torque control, there are four points with high percentage of fuel used as shown in Figure 5.10 *d*). These four points consume about 85 % of the total fuel during 48 % of the driving cycle time. But, Figure 5.10 *d*) do not show the consumption of the fuel to recharge the battery back to its initial charge by using this last control strategy noted by brackets in table 5.1.

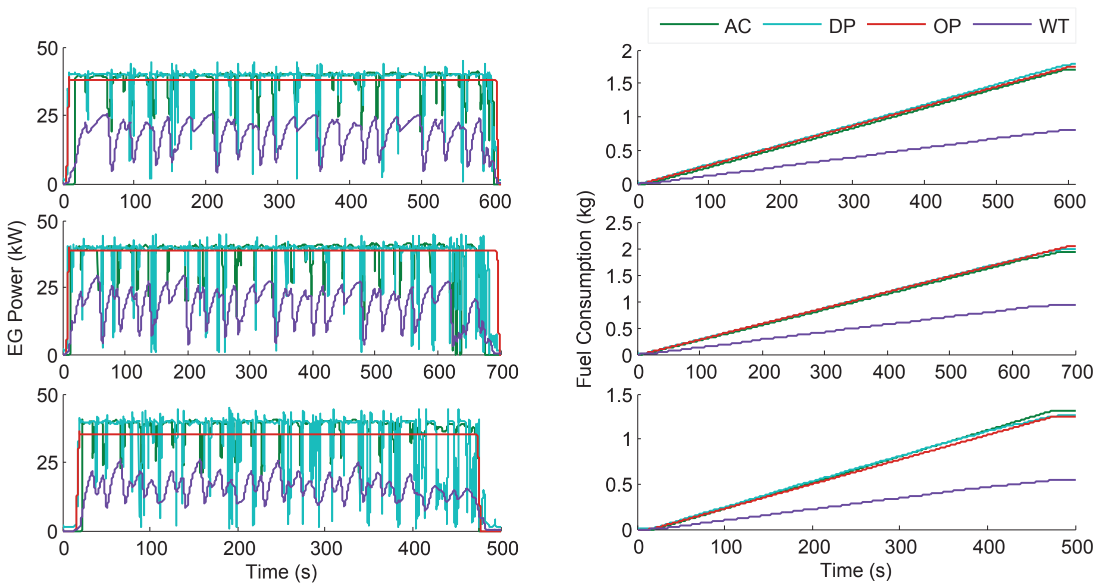


Figure 5.5: Results comparison of the EG power and fuel consumption of the race cycles (MC-Noao1, MCNoao2, MCNoaosp) for all four control strategies.

Actual Control Strategy

As can be seen in Figure 5.11, the actual control strategy will concentrate on the engine operational points at 80 to 90 Nm torque load and 400 to 500 rads^{-1} rotational speed with 71 % of time present at this zone for the racing cycles. It is 80 % of the fuel consumed while it is only 24 % for the road cycles with 9 % spent time.

For the road cycles, 54 % of the fuel consumed is between 400 to 500 rads^{-1} at 70 to 80 Nm torque load with only 21 % of time used at this zone. Most of the 61 % time, the EG will be off with only 1 % fuel consumed at zone less than 400 rads^{-1} and torque less than 30 Nm.

If analysed for all cycles, 84 % of the fuel consumed is between 400 to 500 rads^{-1} at 70 to 90 Nm torque load with 50 % of time present at this zone. So, the engine to be used for this system with the series configuration and this control strategy should be optimised at this zone.

DP Optimised Control Strategy

Using a DP optimised control strategy as depicted in Figure 5.12, the racing cycles will cause 87 % of the fuel consumed to be between 500 to 600 rads^{-1} at 70 to 80 Nm torque load with 77 % present time at this zone.

But for the road cycles, 40 % of the fuel consumed is between 200 to 400 rads^{-1} at 60 to

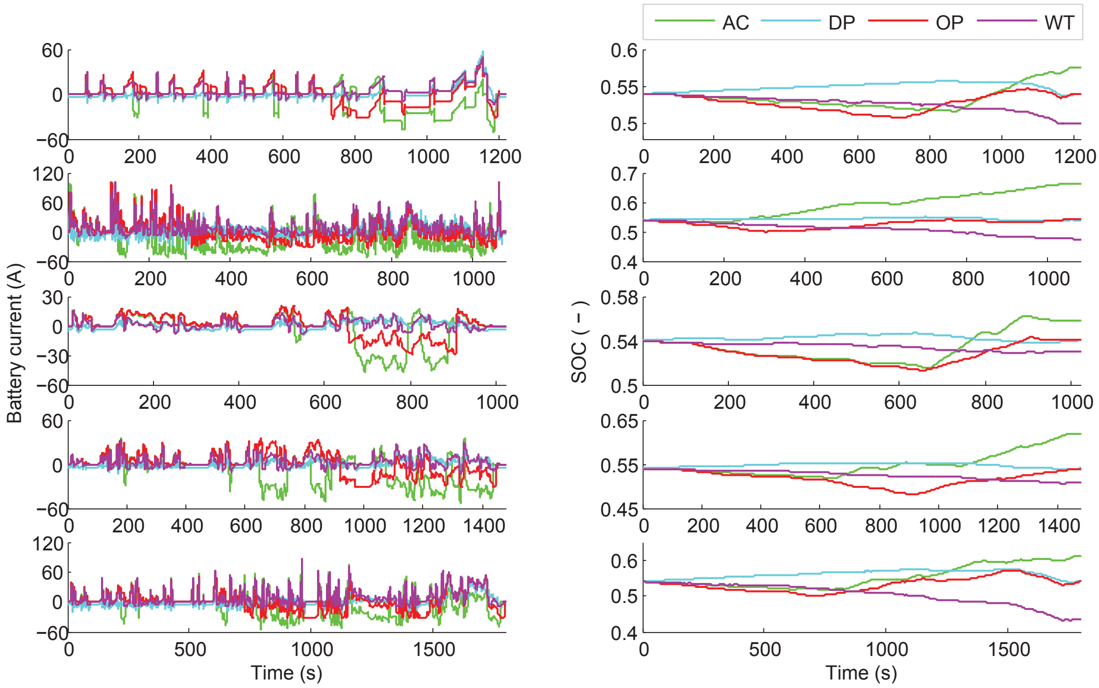


Figure 5.6: Results comparison of the battery current and SOC evolution of the road cycles (NEDC, ARTEMIS, WLTC1, WLTC2, WLTC3) for all four control strategies.

70 Nm torque load with only 8 % of time used at this zone. Most of the 88 % time, the EG consumes 47 % of the fuel at zone less than 200 rads^{-1} and torque less than 60 Nm.

Combined, the recurrent points become three zones for all cycles. 33 % of the fuel consumed is between 500 to 600 rads^{-1} at 70 to 80 Nm torque load with 13 % present time. And 26 % of the fuel consumed is between 200 to 400 rads^{-1} at 60 to 70 Nm torque load with only 7 % time present at this zone. Most of the 64 % time, the engine operates below 200 rads^{-1} at less than 60 Nm torque with 30 % of the fuel consumed.

There will be more transient operation for the EG power as can be seen in Figure 5.5 and Figure 5.7 if using this method to control the engine/generator components. This effect is not preferable for the drivability of the vehicle system. This is because, the calculation of the optimal EG profile is based on a bigger timestep, while for a real-time control it is relatively small. One of the alternative is to modify the objective cost to factors that can eliminate the engine frequent high-low operation power.

On-Off Optimal Control Strategy

In an on-off optimal control strategy, the analysis is more about determining the percentage of engine on time for each driving cycles as can be observed in Figure 5.13. The racing cycles

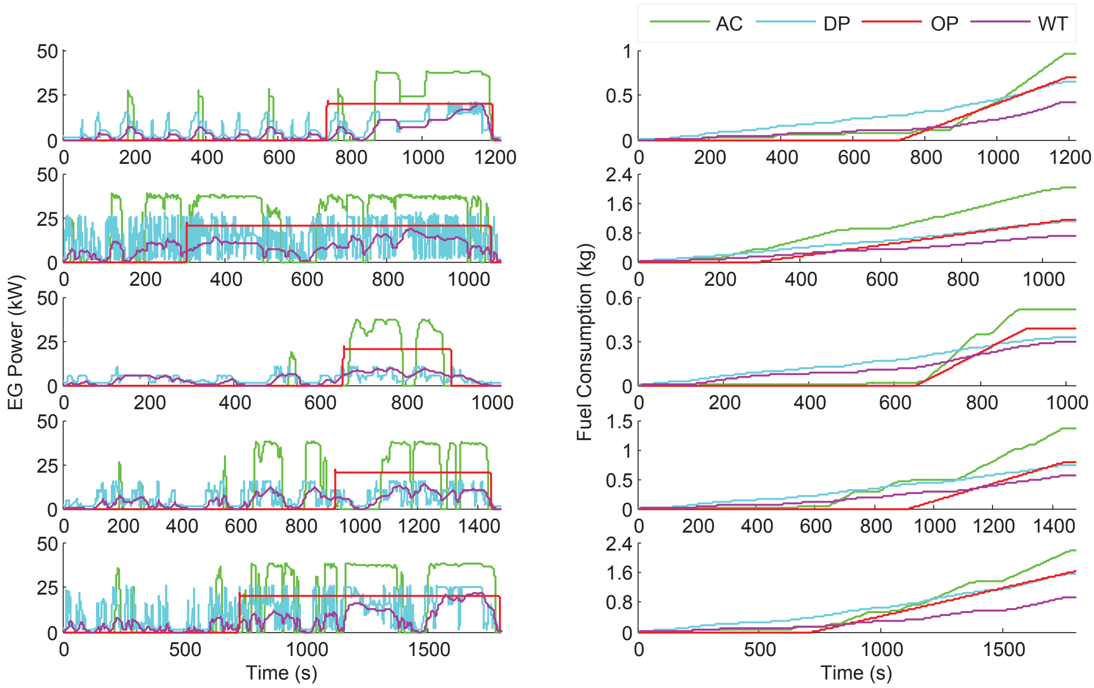


Figure 5.7: Results comparison of the EG power and fuel consumption of the road cycles (NEDC, ARTEMIS, WLTC1, WLTC2, WLTC3) for all four control strategies.

will need the engine to be on all time, but the road cycles on time can ranged from 25 % to 70 % of the driving cycles time.

Engine operations concentrated only on two operational points if using this control. The first is at 60 to 70 Nm, 300 to 400 rads^{-1} and the second is at 70 to 80 Nm, 500 to 600 rads^{-1}. For the racing cycles, 99 % of the fuel consumed is between 500 to 600 rads^{-1} at 70 to 80 Nm torque load with 95 % of time present at this zone. While for the road cycles, 100 % of the fuel consumed is between 300 to 400 rads^{-1} at 60 to 70 Nm torque load with an average of 45 % time used at this zone. Most of the 54 % time, the EG will be off.

Therefore, if it is to be analysed for all cycles, 62 % of the fuel consumed is between 300 to 400 rads^{-1} at 60 to 70 Nm torque load with 28 % of time present at this zone. 37 % fuel is consumed between 500 to 600 rads^{-1} at 70 to 80 Nm torque load with 36 % present time. On the other 35 % time, the engine will be off without consuming any fuel.

So, the engine to be used for this system with the series configuration and this control strategy should be optimised at these two particular zones, at 60 to 70 Nm, 300 to 400 rads^{-1} and at 70 to 80 Nm, 500 to 600 rads^{-1}.

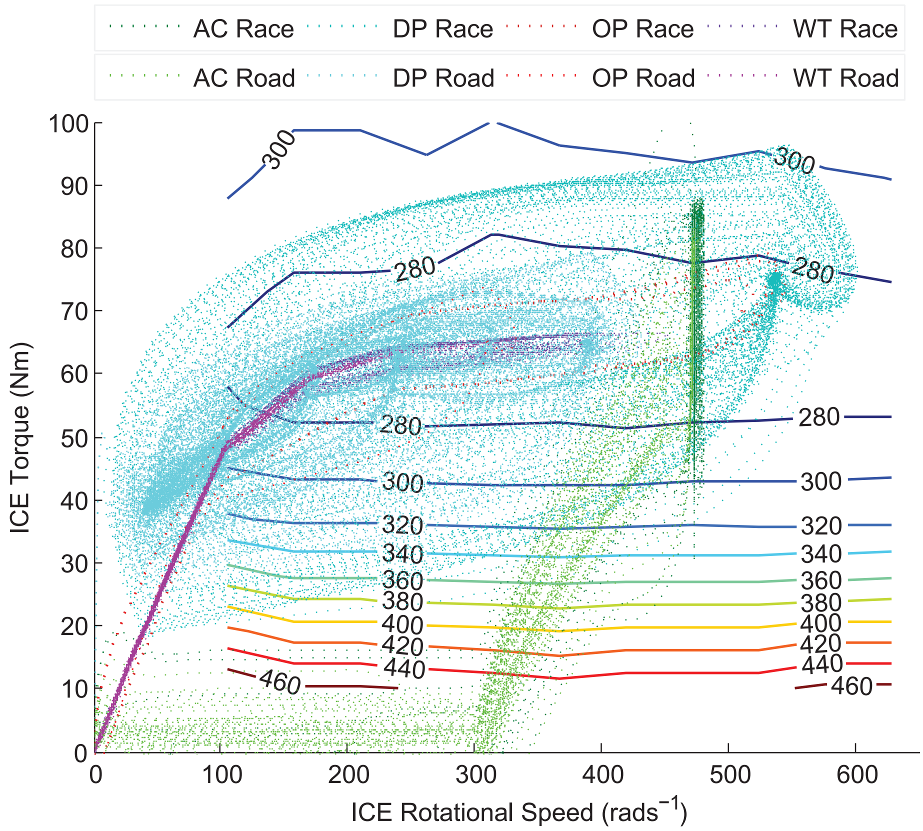


Figure 5.8: Working points of the engine on the BSFC map of all cycles under all four control strategies.

Optimal Torque Control Strategy

The optimal torque control strategy operates the engine mostly at low rotational speed zone below 400 rads^{-1} as presented in Figure 5.14. 84 % of the fuel consumed between 300 to 500 rads^{-1} at 60 to 70 Nm torque load with 73 % present time is the resulting operation by the racing cycles.

For the road cycles, 60 % of the fuel consumed is between 100 to 200 rads^{-1} at 40 to 70 Nm torque load with 40 % of time used at this zone. 25 % of the consumption is between 200 to 400 rads^{-1} at 60 to 70 Nm torque load with only 11 % time used at this zone. Most of 43 % time, the EG consumes 16 % of the fuel at zone less than 100 rads^{-1} and torque less than 50 Nm.

Analyse using all cycles show that 50 % of the fuel consumed is between 200 to 500 rads^{-1} at 60 to 70 Nm torque load with 35 % of time present at this zone. 41 % fuel is consumed between 100 to 200 rads^{-1} at 40 to 70 Nm torque load with 32 % present time. On the other 33 % time,

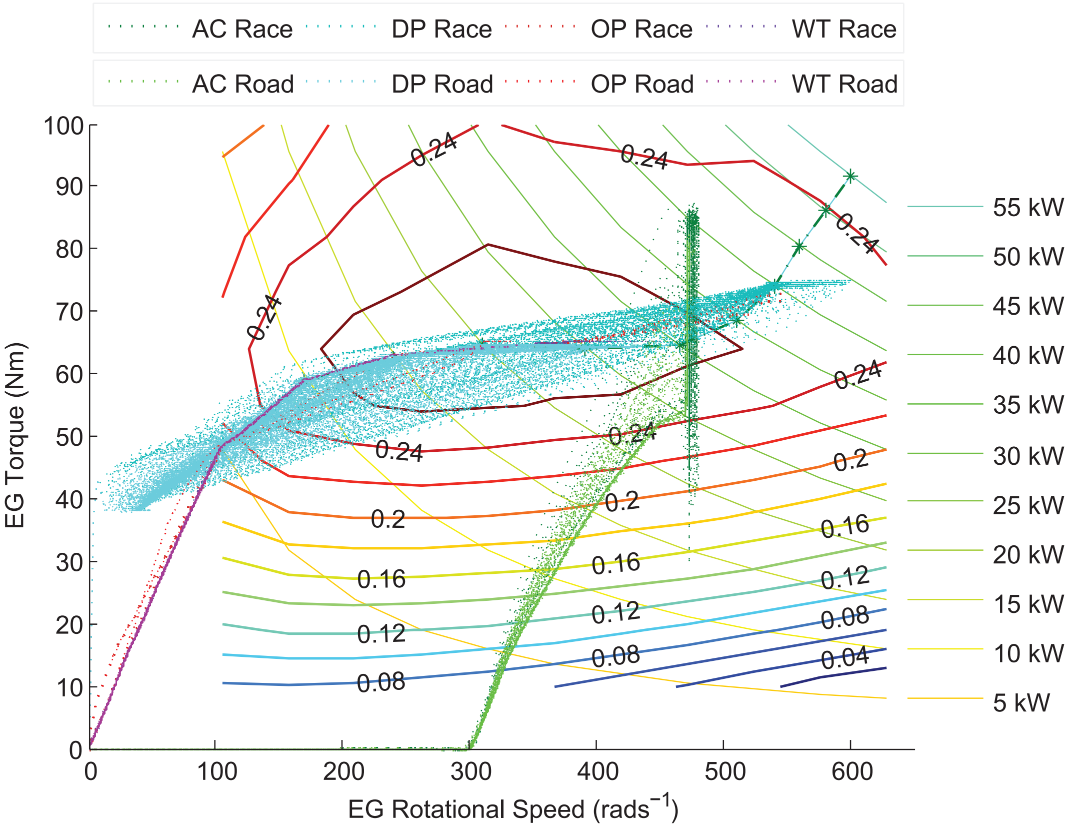


Figure 5.9: Distribution of speed and torque of the generator on the EG map of all cycles under all four control strategies.

the engine operates below 100 rads^{-1} at less than 50 Nm torque with 10 % of the fuel consumed.

If HEV systems is to be designed want to use this control strategy, the engine to be installed for this system should be optimised at zones near its OOP line.

5.3.1 Overall Analysis for All Four Control Strategies

In hybrid vehicles, operational points are predetermined around the engine optimal operating region. It results in five zones which are distinguished in table 5.2:

It is seen that there exists some bias on certain zones because of the control strategy used. For the racing cycles zone 5 consumes nearly half of the total consumption, and at zone 3 for the road cycles. If the engine is optimised at these zones, each 1 % improvement will result about 50 g fuel economy per kg of fuel used. Same deduction can be applied for per kg of the pollutant gases emission.

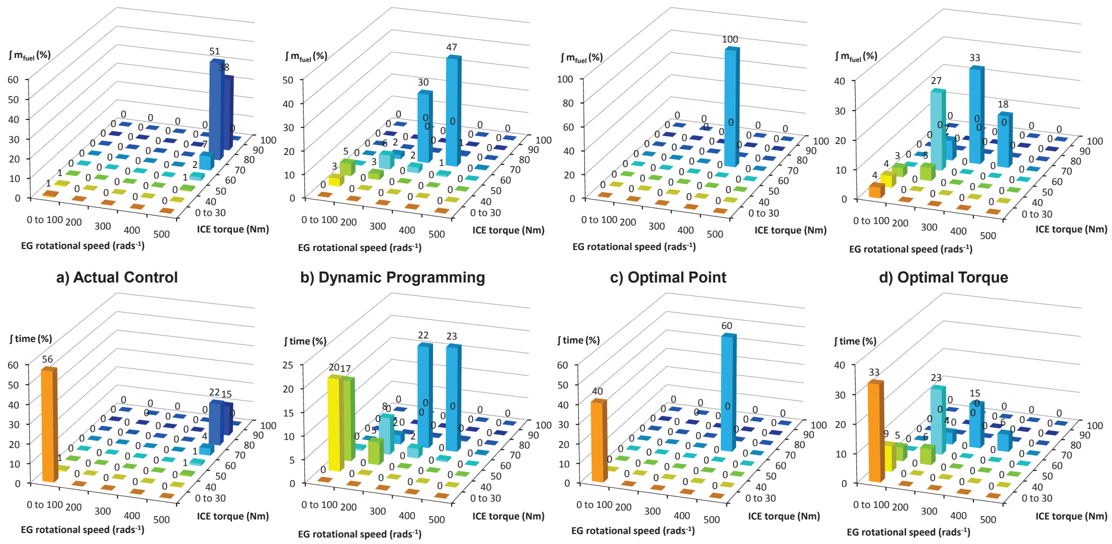


Figure 5.10: Percentage of ICE points distribution of each control schemes for the WLTC3 in terms of fuel consumption and time spent.

Table 5.2: Zones of the engine working points

			Race cycles (%)		Road cycles (%)		All cycles (%)	
Zone	Speed (rad/s)	Torque (Nm)	m_{fuel}	time	m_{fuel}	time	m_{fuel}	time
1	0 to 100	0 to 50	0	5	8	53	5	29
2	100 to 200	40 to 70	3	4	24	21	13	12
3	200 to 400	60 to 70	21	18	43	17	31	17
4	400 to 500	50 to 90	26	24	25	9	25	17
5	500 to 600	70 to 80	47	43	0	0	23	22

In a hybrid vehicle system, the operational point can be concentrated on certain zones because of its degree of freedom to distribute energy, compared to the conventional system with ICE only where the powertrain is coupled directly to the engine and constrained to operate at less optimal point. But hybrid system needs power converters that counteract the system overall efficiency. The biggest portion of its losses comes from the engine which is 0.3 to 0.4, with power converters, electric motor or generator, and transmission have about 0.9 efficiency. The analysis made based on this study will allow an optimization of the engine at the most recurrent point before it is to be installed in a system.

The regenerative capacity depends on the size of the battery and its energy management system. The model utilised can be used to obtain the best sizing of the car components for different application of the car. And this engine working points analysis can be used to determine

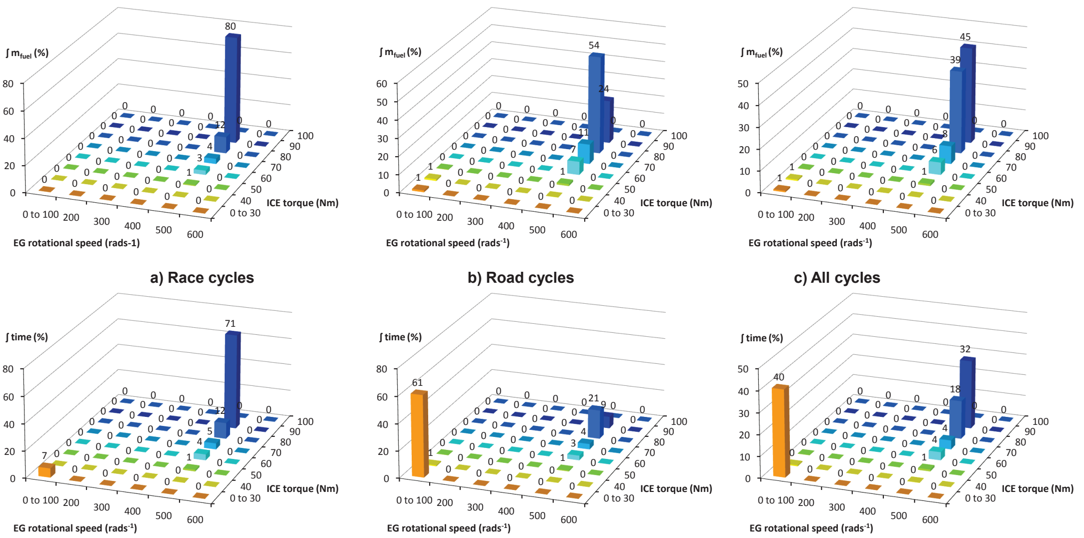


Figure 5.11: Percentage of ICE points distribution for the actual control in terms of fuel consumption and time spent.

the best control strategy for each applications together with its optimal sizing parameters.

5.3.2 Application of the Model and Analysis for Design Optimization

Previously, the analysis is conducted using the actual parameters of the Noao car, a car which is built to fulfill requirement of a competition racing car.

And for the racing application, the best control method for this car is the on-off optimal control strategy. With this control strategy, the car will have a good autonomy, less load for battery, and a good fuel consumption. Also, the components actual parameters are suitable for this application.

But for road application, the optimal torque control strategy is the best control method, it has a good transient operation and low fuel consumption, but it needs some modifications such as higher transmission ratio and a set of rules to limit torque production at low speed and to recharge the battery because of a rapid depletion under this control strategy.

The components actual parameters are overdesigned for a passager car application. So, a retrospective study on the sizing of the battery using the model and analysis method can optimize the system design for road driving cycles application.

In the studied vehicle, the engine is suitable for a normal car utilisation, but the battery is considered to be very big. The battery weight will be reduced if the battery capacity needed for this car is to be reduced. Maybe, changes in the sizing of the car components will impose a change in the control strategy parameters too.

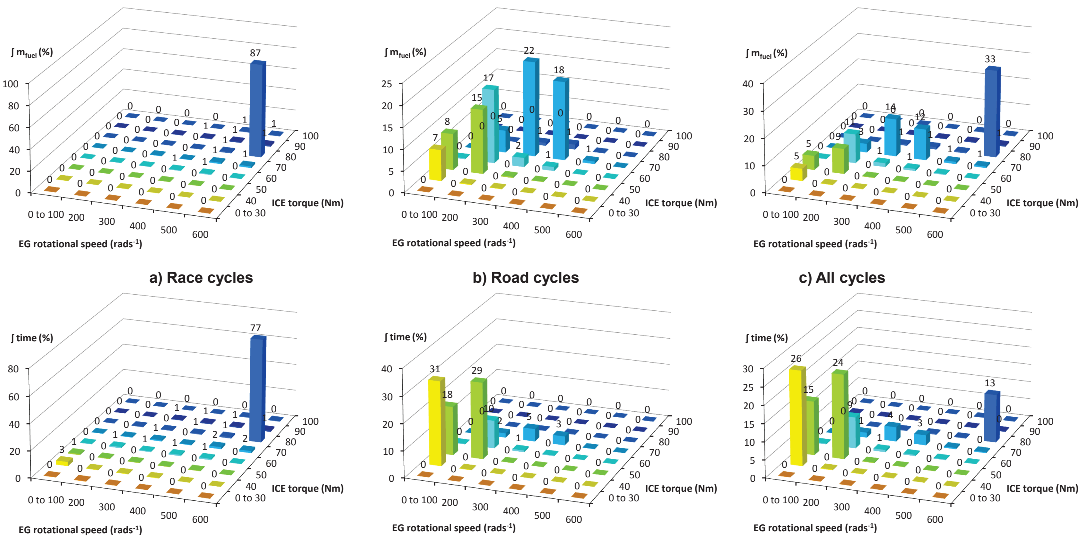


Figure 5.12: Percentage of ICE points distribution for the dynamic programming control in terms of fuel consumption and time spent.

The next study will explain the modification method of the parameters using the most suitable control strategy in order to optimize the vehicle architecture for a normal car application.

Retrospective Method

There are three battery packages in the Noao car. Battery weight is estimated to be 1 kg every cells for a standard vehicle lithium-ion battery cell with 20x20x1 cm dimensions. The number of cells chosen for this study are 141, 129, 117, 105, 93, 81, 69, 57, 45 cells, with a reduction of 12 cells each time which is four cells reduction in each battery packages.

When the battery number of cells are changed, other parameters like the mass of the vehicle and the PI controller parameters of the chassis will be changed as well. The range extender control parameters are kept the same because eventhough the number of battery cells change, for a same driving cycle, the power request will be the same.

A factor is added to the car velocity to define the rotational speed reference in order to coincide more of the range extender operational points at the most efficient point. The value of this factor is chosen to be 1.2 because like shown in the previous analysis using the optimal torque control strategy, the engine maximum rotational speed is nearly 500 rads^{-1} and the maximum speed of the range extender can reach until 600 rads^{-1}.

NEDC, ARTEMIS, and WLTC3 driving cycles are chosen for this retrospective method. The target autonomy range is about 100 km. For the simulation, the initial SOC is taken to be 0.54. The autonomy range is calculated based on the distance the car can be driven with a battery

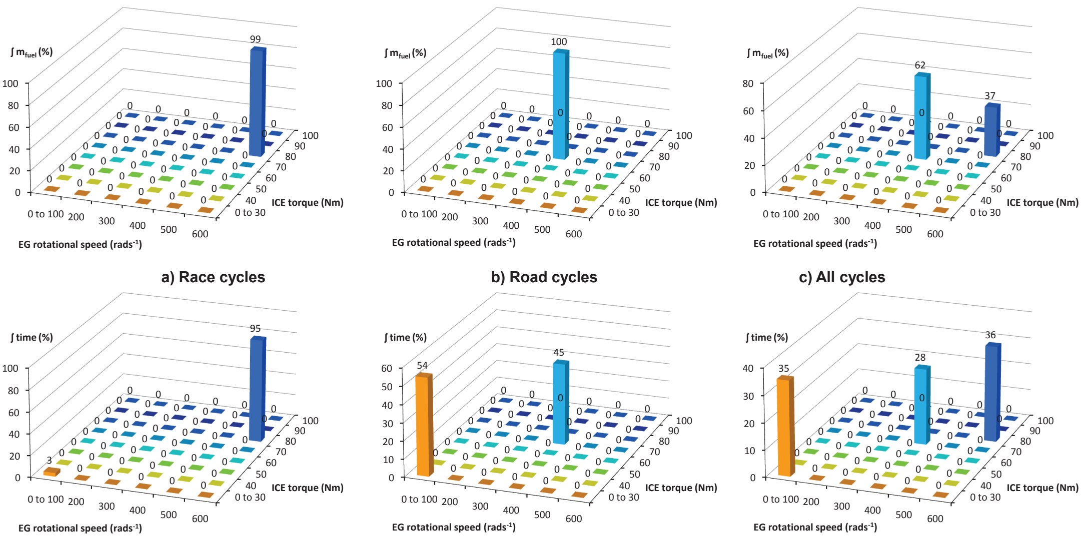


Figure 5.13: Percentage of ICE points distribution for the on-off optimal control in terms of fuel consumption and time spent.

charge depletion from 0.9 SOC to SOC of 0.3.

Results and Discussion

The results of the retrospective study are presented in table 5.3 concerning the final SOC value, the fuel mass to recharge the battery back to its initial charge of 0.54, and the autonomy range of the car under different number of cells of the battery packages.

Using the modified optimal torque control strategy, the fuel consumption for the NEDC cycle is 0.528 kg, 0.876 kg for the ARTEMIS cycle, and 1.159 kg for the WLTC3 cycle. The final SOC decreases when the number of cells are decreasing which causing the fuel mass to recover the energy used during the driving cycles to be increasing in function of the reduced number of cells.

The autonomy range is shorter for a less number of battery cells. The number of cells that can give more than 100 km autonomy for all three driving cycles is about 60 battery cells.

The reference EG power to be given by the range extender during all three cycles is depicted in Figure 5.16. Under these driving cycles, the maximum EG power is only about 30 kW. A piecewise control algorithm can be used to improve the power response using the parameters defined for the control of the range extender power.

The voltage and current of the battery is shown in Figure 5.17 with different number of cells for the NEDC, ARTEMIS, and WLTC3 driving cycles. The battery voltage will drop to a lower rate for a fewer number of the battery cells. It is at 550 V when the battery have 141 cells but only 180 V when it have 45 cells.

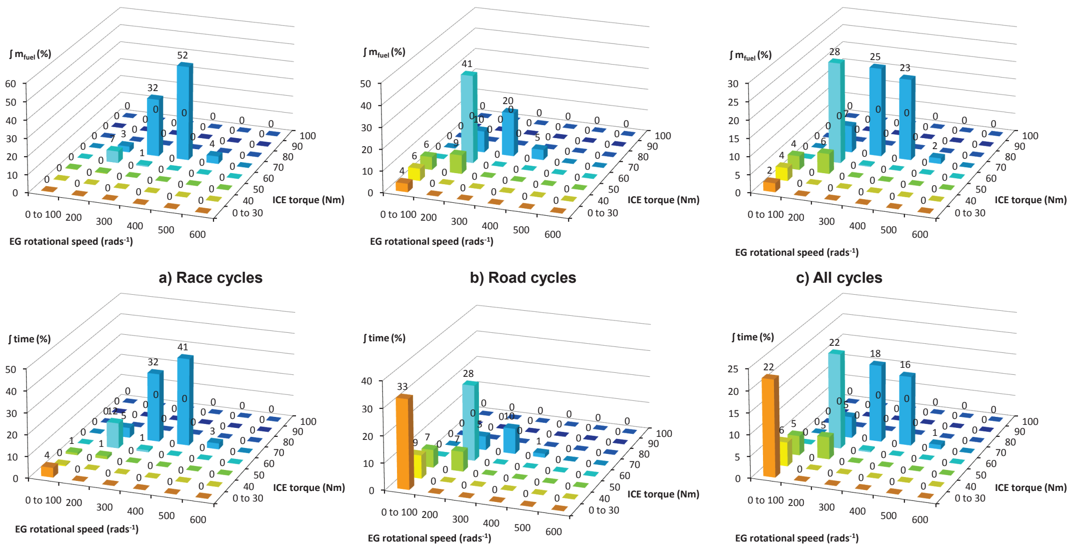


Figure 5.14: Percentage of ICE points distribution for the optimal torque control in terms of fuel consumption and time spent.

For this simulation, the battery current limit is imposed to be 100 A. But, it looks like this limit can only be respected if the battery cells are more than 90 cells. The battery will need a better battery management system if the cells to be reduced lower than 90 cells because there will be current shot up during the ARTEMIS and WLTC3 cycles.

As stated before, the engine operational points will be the same for a same driving cycle but different battery number of cells. They are presented in Figure 5.18 for each cycles and in Figure 5.19 for the combined analysis.

In Figure 5.18, most of the fuel consumed is at the zone 3 of the working points for all three driving cycles. But the most recurrent point is at zone 1 for the NEDC and WLTC3 cycles with 44 % and 28 % of the time respectively, which suggest the pollutant emissions at this point are to be survey closely. Or, the operation at this point is easier to be reduced with a simple control algorithm.

In Figure 5.19 the engine operational points is concentrated at the zone 1 during most of the time. Zone 2 and zone 3 are the points with the most fuel consumed. But these points are not yet coincide the optimal operating point with just 19 % of the fuel consumed and 7 % time present at this point during the driving cycles. Maybe, if the fuel consumed to recharge the battery to its initial SOC after the cycles are finish is taken into account, the optimal point will be the point with the most fuel consumption.

In this part, the system is studied for another application of this vehicle with a lower rating power. For a road usage, NEDC, ARTEMIS, and WLTC3 driving cycles are used to determine

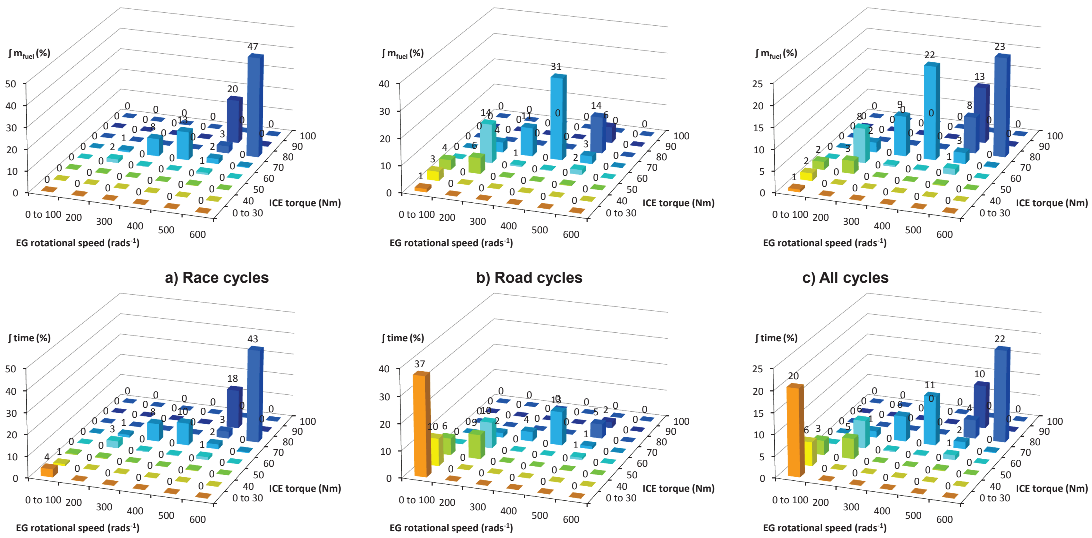


Figure 5.15: Percentage of ICE points distribution for all control strategies in terms of fuel consumption and time spent.

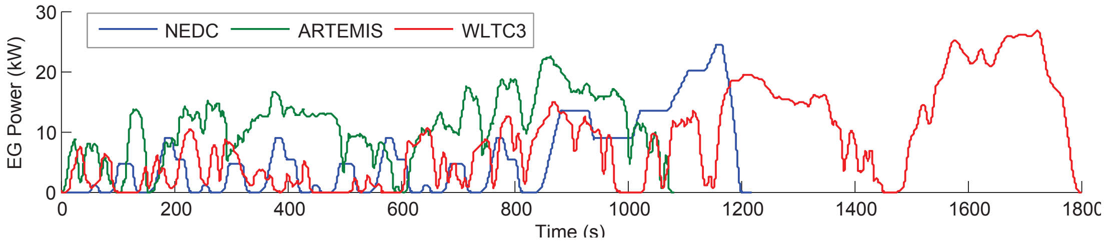


Figure 5.16: Given EG power for the three road cycles; NEDC, ARTEMIS, and WLTC3 under the modified optimal torque control strategy.

the optimal number of battery cells suitable for this application. An adequate number of battery cells is between 60 to 90 cells.

The engine to be used in this type of system, for this application, using this control strategy should be optimised at zone 1, 2, and 3 like mentioned in table 5.2.

The analysis on the results of the retrospective method allow us to envisage the precautions to take when resizing a component for a system of hybrid vehicles. Lighter and smaller battery packages is less imposing and its thermal control is easier to design.

Table 5.3: Results of the retrospective method.

Number of cells	141	129	117	105	93	81	69	57	45
NEDC									
Final SOC (-)	0.520	0.516	0.514	0.512	0.509	0.505	0.500	0.492	0.481
Recharge m_{fuel} (kg)	0.044	0.052	0.056	0.061	0.067	0.076	0.087	0.104	0.127
Autonomy (km)	323	274	253	233	210	187	162	136	111
ARTEMIS									
Final SOC (-)	0.504	0.502	0.499	0.495	0.490	0.484	0.476	0.468	0.460
Recharge m_{fuel} (kg)	0.077	0.083	0.090	0.098	0.108	0.121	0.137	0.155	0.174
Autonomy (km)	290	271	250	228	206	184	163	144	123
WLTC3									
Final SOC (-)	0.476	0.471	0.465	0.458	0.449	0.436	0.420	0.398	0.373
Recharge m_{fuel} (kg)	0.137	0.148	0.161	0.177	0.198	0.224	0.261	0.308	0.363
Autonomy (km)	219	203	187	170	153	135	116	98	84

5.4 Conclusion

In this chapter, four widely used control strategies for HEV systems have been identified and tested on a dynamic model that have been developed in the previous chapter. The control strategies are; the actual control strategy, the DP optimized control strategy, the optimal point control strategy, and the optimal torque control strategy.

Race driving cycles and road driving cycles are the two types of driving cycles studied in the analysis of the HEV operating points. It analyses the different ways to control a system and how a system energy is consumed in order to identify the most suitable control strategy for each applications and define its possible improvements.

The analyis consists of determining the amount of fuel at a particular zone and weighted its impact for further engine improvements. The time spent at a particular points are also quantified for further use to identify the zone of recurrent working points that will be useful to reduce emissions of green house gases.

Then the model and the analysis method is used to determine an optimal control and sizing for a normal car application. This is done by reducing the number of battery cells in the car. The autonomy limit becomes one criteria to determine the optimal sizing of the battery.

If using the same control parameters to determine the torque and the speed reference of the range extender, it will results in the same operating points for a same driving cycle eventhough the battery cells are reduced. But this will cause the battery packages voltage to drop and its current to increase in function of decreasing number of battery cells.

The analysis method and the retrospective method are useful to study and identify the most

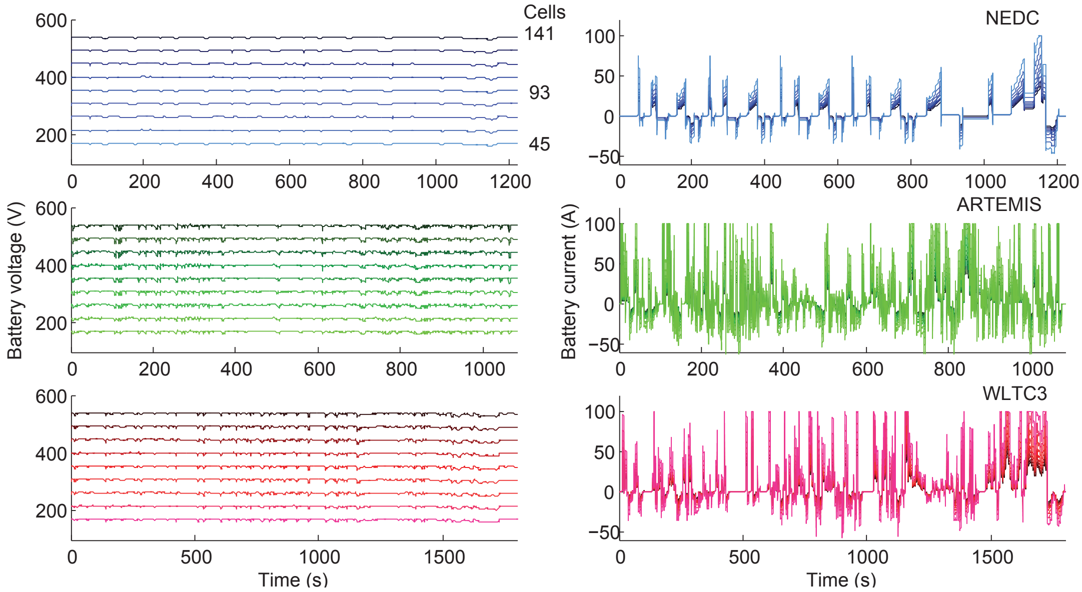


Figure 5.17: Battery voltage and current response for the three road cycles; NEDC, ARTEMIS, and WLTC3 if the number of battery cells are reduced.

suitable control strategy, the modifications to be taken to the control algorithm, the right sizing of the system's components for a particular utilisation, and the improvements to be effectuated on the engine operational zones that will give the biggest impact after optimization in order to obtain a better energy efficiency of the system.

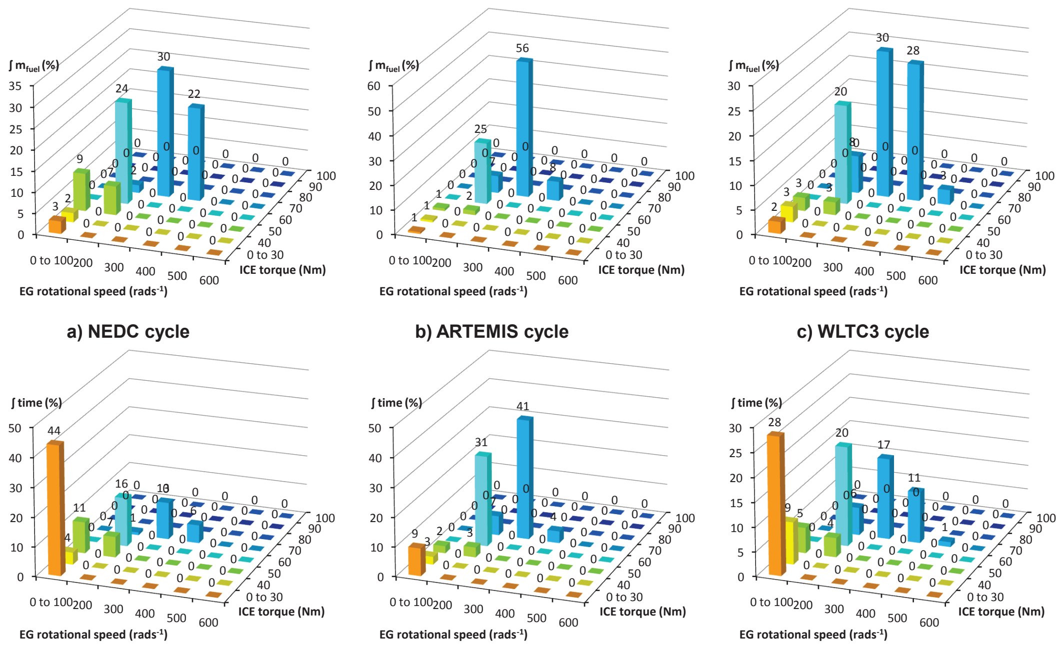


Figure 5.18: Percentage of ICE points distribution for the three road cycles; NEDC, ARTEMIS, and WLTC3 in terms of fuel consumption and time spent.

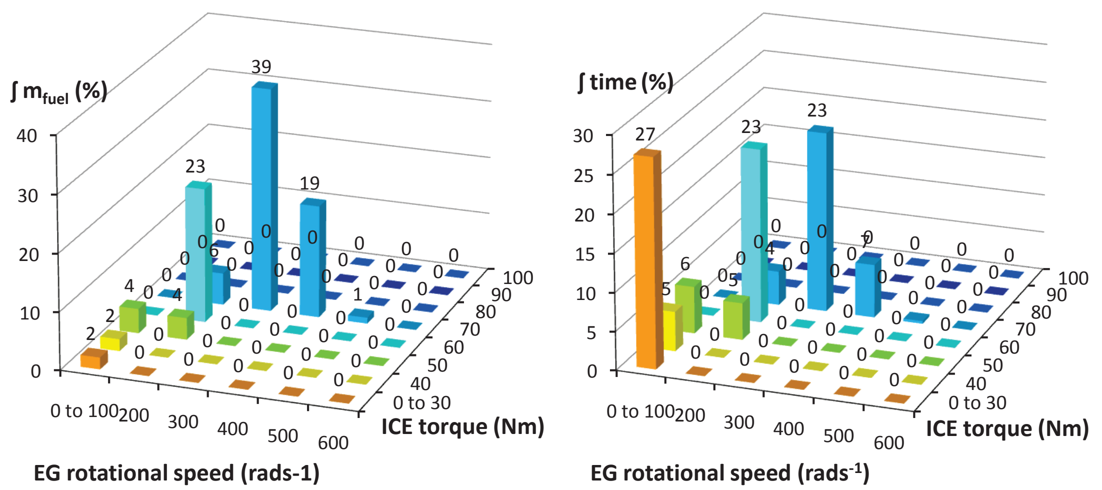


Figure 5.19: Percentage of average ICE points distribution for the three road cycles in terms of fuel consumption and time spent.

Whatever the mind can conceive and believe, it can achieve.

- Napoleon Hill

Chapter 6

Conclusion and Perspectives

In the first chapter, a review on hybrid vehicles, the modelization method, and its control strategies are documented in this part of thesis for the literature review. Since the first development of HEV system, various architectures, energy sources, and control strategies have been developped and tested in order to improve efficiencies of this system. And this will continue as long as the whole world is concerned with the global warming and climate changes that are now also affecting our routine life. With new technologies that can be used to predict vehicles journey and energies consumption, an optimal energy management can be executed easily.

After the reviewing phase, comes the development of the vehicle model, started with a quasi-static model, then a dynamic model that can well represent the real behavior of the system like in its real system. The dynamic model is developed using EMR method according to the system physical causality. Verification of models are made by comparing results obtained in the experiments and drive tests carry on for this competition car on a real racing circuit. In the first step, with the same control strategy, optimization is applied by changing the working point of the engine and generator. Then, the model is used to test an integration of a fuel cell stack system as a range extender of the hybrid car system which is still in study level for the system to be build.

The next chapter is the control strategy optimization method and the development of a tool to predict driving cycles of the car for competition purpose on racing tracks. DP is used to optimized the actual control strategy of the system on the known driving cycle obtained from experiments of the studied car. The driving cycle prediction method is deducted from the driver's actions on pedal on certain zone of a circuit. This will need the dynamic model to be simulated part by part in order to match the distance covered and the time completed.

In the fifth chapter, the model is used to test and compare applicable and feasible control strategies for the system through simulation. Analysis of the engine working points under different control strategies and its consumption trend for the studied system are analysed. Then, a retrospective method to design a same vehicle architecture but for other application is studied. The advantages of this method is that it is done by using a well established model as reference to design other architectures or control strategies. This model and analysis method can be applied to design a better hybrid vehicle system in terms of the sizing, control strategy, and optimized components.

As perspectives, the model developed can be used to study this system for a different racing applications or to develop hybrid vehicle system with other architectures. The ICE can be optimized by experts and specialists of engines development in order to obtain a better energy efficiency and lower emissions of green house gases.

EMR is a good method to represent dynamic model and it can be used to modelize any electromechanical machines. The implementation of EMR can be envisaged to model other system than a vehicle system, like a renewable energy system, a new electro-mechanical system or a robotic system.

In the past decades, thermal engines have been the most utilised power source used in vehicles because of its compactness i.e power to weight ratio and power to volume ratio. Until now, thermal engines for conventional vehicles have also been optimized and have reach a better efficiency for present system and its utilisation will continue. But, due to environment concern, focus has been given to the development of electric vehicles, but this type of system is still expensive and have a long way to be adopted well by consumers. Maybe, the emerging HEV system is not an end of the thermal engines utilisation, but it is just the beginning of an efficient utilisation of the thermal engines for a better future of the environment if it is well collaborated with other power sources and power converters.

Chapter 7

Resumé de la thèse en Français: Modèle de simulation efficace et nouvelle stratégie de contrôle pour améliorer l'efficacité énergétique dans les véhicules hybrides électriques terrestres

Introduction

Motivation

Un véhicule électrique hybride (VHE) a au moins deux sources de propulsion [1, 2, 3, 4]ou types de stockages d'énergie, des convertisseurs, avec au moins l'un d'entre eux pouvant fournir de l'énergie électrique [2, 5]. Grâce à la présence d'un système réversible de stockage d'énergie (ESS) et de machines électriques (ME), les VHEs offrent une capacité de freinage régénératif, de la puissance assistée, et une réduction de la cylindrée [6, 7]. Le VHE apparaît comme l'une des technologies les plus viables avec un potentiel important pour réduire la consommation de carburant économiquement réaliste avec la contrainte des infrastructures et l'acceptation des clients [8].

Le système VHE a de nouveaux degrés de liberté pour délivrer la puissance [7, 8], parce que l'ESS offre la possibilité de stocker une partie de l'énergie produite par le moteur et de l'utiliser en cas de besoin. En outre, l'ESS possède des avantages de zéro émission, d'indépendance du pétrole brut, et un faible coût d'exploitation [9]. D'autre part, l'utilisation d'un moteur électrique couvre une plage de fonctionnement inefficace du moteur à combustion interne (MCI) [10, 11] et est conçu pour gérer les variations transitoires de puissance. Par conséquent, le MCI fonctionne à sa combinaison optimale de vitesse et de couple [12, 13], ce qui permet un fonctionnement du MCI constant, une possibilité d'économie de carburant, des émissions de gaz d'échappement moins polluants [8] et une réduction des émissions nocives [14, 15, 10]. Le VHE peut diminuer les émissions de gaz à effet de serre et l'effet du réchauffement climatique, alors que les combustibles fossiles représentent encore 85 % des sources d'énergie dans le monde et est la source d'énergie la moins cher [16].

Le VHE a de grandes capacités comme nouveau moyen de transport alternatif [17, 15, 13] pour la mobilité durable [4] et est considéré comme un véhicule ayant les émissions les plus faibles [18]. Les recherches sur les véhicules électriques hybrides sont devenues importantes en raison de préoccupations concernant le changement climatique [14], la protection de l'environnement [3, 19, 20], la législation de plus en plus stricte concernant les émissions carbones [21], et les préoccupations environnementales sur la contamination de l'air urbain causés par la fumée noire, les hydrocarbures et les oxydes d'azote (NO_x d'autobus et de camions à moteur diesel) [22, 4].

Ils sont également considérés comme l'une des solutions efficaces pour apporter une solution au problème de pénurie d'énergie [4, 21], des éxigences croissantes sur la capacité de combustibles fossiles ainsi que son prix [3, 14, 21]. Ils peuvent également apporter des solutions au problème de la conservation de l'énergie [20] car ils ont une plus grande efficacité de carburant [19] et peut améliorer l'économie de carburant [15, 9, 8, 10, 17, 14, 12]. Le VHE possède de meilleures performances par rapport aux véhicules conventionnels [14, 21]. Aujourd'hui, la tendance de la consommation d'énergie électrique a augmenté et la plupart des appareils électriques remplacent les composants mécaniques ou hydrauliques dans le véhicule. Les clients attendant plus de performance [23, 21], de confort et de sécurité de ces nouveaux systèmes [23].

Il y a de nombreux avantages qu'un système VHE [24] peut offrir par rapport à un véhicule conventionnel. En véhicule conventionnel, la conception du MCI est plus lourd, il est dimensionné pour la demande de puissance de pointe, son fonctionnement à une plus haute efficacité est dans une fourchette étroite, sa courbe de puissance est limitée à une bande de vitesse et ses freins mécaniques dissipent l'énergie cinétique sous forme de chaleur [12]. Dans un système VHE, le MCI est plus petite [12], plus léger, plus efficace, et dimensionnés pour la puissance moyenne.

Le MCI peut fonctionner avec la plus haute efficacité et peut ainsi fournir une plus grande économie de carburant et de réduction des émissions due à la consommation de carburant qui mènent à l'amélioration de l'air et de la santé humaine. Cela peut réduire l'usure sur le moteur, et la réduction de la pollution sonore causée par un fonctionnement du moteur à faible vitesse. La courbe de puissance du ME est mieux adaptée à vitesse variable et peut donc fournir plus de couple à basse vitesse. Le ME dans un VHE peut récupérer une partie de l'énergie cinétique et la stocker dans les batteries via le système de récupération au freinage, donc de réduire l'usure des freins [12].

Alors même que le VHE est considéré comme la meilleure solution pour le futur mode de transport, il reste néanmoins des études àfaire, des expériences, des applications de simulations pour un dimensionnement précis ainsi que le développement d'algorithmes de contrôle [8], parce que la stratégie de contrôle et le dimensionnement de ses composants peuvent affecter les performances du véhicule [20]. Le système VHE a une architecture complexe [8], un degré élevé de flexibilité de contrôle [10], une gestion complexe de l'alimentation [20, 10], et il nécessite la coordination des ME et MCI [18] pour améliorer l'économie de carburant et réduire les émissions [4]. De plus, il en résulte un coût initial élevé [16, 9] pour construire un système équipé d'une combinaison de batterie, MCI, EM, onduleurs, pile à combustible ou supercondensateur.

VHE peut parvenir le besoin des consommateurs et il a une valeur ajoutée, mais ses pertes d'énergie transmise par des sources à ses charges doivent être minimisés [16]. Et l'utilisation d'une batterie comme ESS, nécessite un long temps de charge et a une courte durée de l'autonomie [9] parce qu'il ne peut pas supporter tout le trajet [4] en raison de la capacité de la batterie qui est limitée à son poids et le coût. Le MCI doit démarré et s'arrêté fréquement, et son efficacité moyenne est affectée par des transitoires au début et de fin de son cycle de charge [25].

Il ya de grands défis pour la mise en œuvre de la gestion de l'énergie (EMS) et de la distribution de couple du VHE. Le plus important est de répondre à la demande de couple du conducteur tout en réalisant la consommation et les émissions de carburant satisfaisante. Dans le même temps, il doit maintenir l'état de charge de la batterie (SOC) à un niveau satisfaisant pour permettre la livraison effective de couple sur une large variation de situations de conduite [15, 9]. Par rapport à un système classique de MCI, VHE intégre plus d'appareil électrique dans son système tels que les machines électriques, électronique de puissance, les transmissions électroniques à variation continue, les contrôleurs de groupes motopropulseurs intégrés, dispositifs de stockage d'énergie de pointe et des convertisseurs d'énergie [16]. Il a plus de degrés de liberté qui rend la gestion de son énergie compliquée et a besoin d'une étude approfondie avant de pouvoir être mis en œuvre dans un véhicule réel.

Une stratégie de gestion de l'énergie appropriée est nécessaire pour coordonner les sources d'énergie avec des multiples convertisseurs [3] et maintenir la santé de la batterie [4]. Le rôle d'EMS est de trouver le moyen le plus efficace de diviser la demande de puissance entre le moteur et l'ESS, et décider comment diviser cette demande de puissance totale entre les sources à bord [7, 4]. Pour obtenir une efficacité énergétique maximale, et optimiser plus le fonctionnement du moteur primaire, nous devons améliorer l'efficacité des composants électriques et/ou la gestion de l'énergie [23] car l'amélioration de l'économie de carburant dépend fortement de sa stratégie de contrôle [26].

Avec les problèmes comme le réchauffement climatique, les émissions nocives des moteurs thermiques, moins de ressources de combustible fossile, et l'augmentation du prix du carburant, nous sommes toujours en recherches de mèthodes de consommation efficaces des ressources naturelles. Mais, ces ressources ne dureront pas longtemps si aucun effort n'est fait pour ralentir la tendance actuelle. Un développement d'un nouveau système ou une nouvelle méthode prend du temps pour s'ancrer dans la vie de tous les jours. L'essai et le prototypage rapide d'un système peut se faire assez rapidement avec l'utilisation d'outils de modélisation et de simulation. Et cela peut nous permettre d'explorer de nouvelles alternatives pour économiser du carburant. Avec tous les efforts qui ont été initier dans tous les secteurs pour réduire les émissions de polluants et une nouvelle législation sur les émissions de véhicules, les véhicules électriques hybrides sont l'une des meilleure alternatives à bien répondre à cette attente.

Objectifs et cadres

Le travail tourne autour de quatre mots clés : véhicule hybride électrique, modélisation efficace, stratégie de contrôle optimale et efficacité énergétique.

Les principaux objectifs de ce travail sont de développer une méthode de modélisation efficace pour un déploiement facile d'une stratégie de contrôle, examiner et étudier une stratégie de contrôle optimale pour une application spécifique, et analyser l'amélioration qui peut être effectué au MCI pour une meilleure efficacité de l'architecture hybride.

Les cadres de ces travaux comprendront la partie de simulation du système étudié et sa validation avec les résultats expérimentaux. Les études de cas sont utilisées pour analyser l'optimisation qui peut être effectuée au système d'origine. L'optimisation pourrait être une optimisation des paramètres de contrôle ou d'un remplacement de certains composants du système afin d'obtenir une meilleure efficacité du système grâce à la simulation.

Ensuite, une étude plus spécifique sur la méthode pour améliorer la stratégie de contrôle d'origine du système sera étudiée. Un outil d'optimisation bien établi sera choisie pour optimiser la stratégie de contrôle effective et deviendra un point de repère d'une nouvelle stratégie de contrôle optimale pour être déployé dans le système. Une méthode pour connaître la consommation d'énergie du système sera développée afin d'obtenir un contrôle optimal adapté à la demande du véhicule.

Les principales composantes du système seront étudiées pour des améliorations de l'efficacité énergétique. Dans ce travail, les sources d'énergie du système sont converties par le MCI et stockées dans la batterie. En utilisant le modèle mis au point, l'analyse sera menée pour identifier une stratégie de contrôle optimale pour une utilisation spécifique. Des améliorations peuvent être envisagées sur certaines zones de la zone opérationnelle de MCI basée sur l'analyse des points de fonctionnement récurrents du moteur. Ensuite, un dimensionnement optimal des paquets de batterie pour une autre application pourront facilement être trouvés en utilisant le modèle.

Organisation de la thèse

Cette thèse est composée de quatre chapitres principaux en plus de l'introduction (premier chapitre) et la conclusion/perspectives (dernier chapitre).

Le deuxième chapitre fera état des différents types de véhicules et les architectures, les outils de modélisation, et des stratégies de contrôle existantes.

Le troisième chapitre présentera la méthode de modélisation du système et de sa validation. Il commence par une méthode simple d'un modèle quasi-statique et se poursuit avec un modèle dynamique utilisant une méthode représentation énergétique macroscopique (REM). Ensuite, un remplacement des composants du système étudié par la simulation est présentée.

Le chapitre quatre présentera une optimisation de la méthode de stratégie de contrôle et la prévision actuelle de la consommation d'énergie du système.

Et enfin, le chapitre cinq étudiera quatre stratégies de contrôles largement utilisées dans le système VHE et les améliorations possibles grâce à l'analyse du fonctionnement du MCI et son application pour concevoir un meilleur système pour d'autres applications véhicules.

Revue sur les véhicules hybrides

Introduction

Un système VHE est un système complexe qui peut être construit en diverses architectures, configurations et combinaisons. Pour identifier ses types et fonctions, le développement de ce système peut être facilement effectuée et réalisée. Mais, le système VHE n'est pas seulement un système physique, il a besoin d'une gestion efficace de l'énergie pour contrôler le flux de puissance dans son groupe motopropulseur. Ceci est connu comme la stratégie de commande du système.

Une bibliographie de la stratégie de contrôle qui a été employé dans le VHE développés sera présenté dans une section de ce chapitre. Cela nous aidera à identifier quelles stratégie de contrôle est adapté pour une utilisation et une configuration spécifique, et quelle mesure prendre pour obtenir une stratégie de contrôle optimale qui peut être mise en œuvre dans un véhicule réel. Et enfin déterminer quelle stratégie de contrôle est mieux adaptée à notre système développé.

Types de véhicules et d'architectures

Un certain degré d'hybridation (DOH) fournit une mesure quantitative de l'endroit où la puissance circule dans un véhicule hybride. Cela permet à un concepteur de décider quel type de stratégie de contrôle d'être utilisé et les composants à contrôler.

Zéro DOH désigne un système de véhicule avec seulement un CI et un DOH d'un un véhicule électrique complet comme la batterie, la pile à combustible, ou d'un véhicule à panneau solaire. Dans Figure 7.1 chaque type de véhicules utilise une partie différente des énergies provenant de sources diverses en fonction de son sytème de propulsion. Son application et son DOH deviennent un facteur important pour l'optimisation; l'efficacité ou l'électrification.

Sources d'énergie utilisées dans les applications pour véhicules hybrides électriques

Un choix de sources d'énergie utilisées dans le VHE dépend de son application et les avantages de leur utilisation. Les moteurs diesel sont généralement choisis pour une utilisation dans les

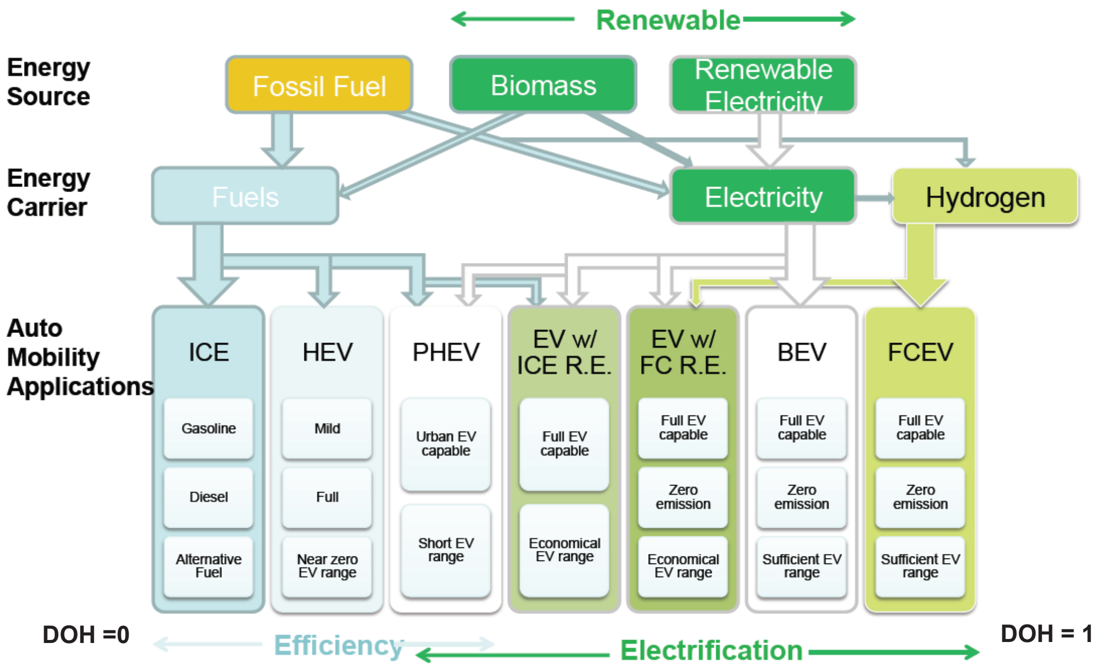


Figure 7.1: Représentation schématique de types de VHE avec écoulement dans les sources d'énergie et de concentration de conception (extrait iTEC 2012 petit cours sur VHE Fundamentals par M. Zhang) [27].

véhicules lourds comme les autobus et les camions. Et une batterie lithium-ion est privilégiée car elle a une plus grande puissance au rapport de poids comparé à d'autres types de batteries.

Outils et méthodes de modélisation

Le développement de la technologie informatique a conduit à une explosion d'une modélisation sur ordinateur pour simuler et prédire le comportement de machines ou de systèmes réels. L'utilisation de la simulation a des avantages d'un prototypage rapide, la conception rapide et la mise en œuvre d'un système, avec un coût de développement moins coûteux et un temps de développement réduit.

Un modèle de simulation peut être réalisé en un seul modèle de composant ou en un modèle global. Certains modèles sont conçus pour concevoir un dispositif de commande en temps réel d'un système. Mais, un modèle de simulation n'est pas valide sans vérification avec son système physique. Normalement, cela peut être fait en comparant ses résultats avec des résultats expérimentaux à partir d'un banc d'essai ou à une installation hardware-in-the-loop (HIL).

Dans la simulation, il existe trois principaux types de méthodes de modélisation; la méthode de létat stationnaire, la méthode quasi-statique et la méthode dynamique. Le modèle état stationnaire est utile pour l'analyse au niveau du système et évaluer le comportement à long terme du véhicule [53]. Moins de temps de calcul est nécessaire, car elle néglige tous les états transitoires et utilise des tables de consultation pour représenter ses données expérimentales [54]. Un modèle dynamique équivalent ajoutée à un modèle à l'état stationnaire constitue un modèle quasi-statique. Il est généralement utilisé dans l'optimisation globale de gestion de l'énergie [54]. Cette approche a été utilisée pour développer PSAT [30], ADVISOR [55], et QSS Toolbox [40, 35] pour l'analyse des systèmes et la méthode de conception de VHE.

Un modèle dynamique tient compte des états transitoires et peut étudier de grandes transitions de charge qui se produisent au cours du changement de vitesse ou d'accélération rapide [53, 54, 56]. Le modèle est plus précis et plus complexe provoquant un temps de calcul élargie, car il nécessite des informations précises sur les caractéristique et l'environnement du système [57, 58, 53, 35]. Il peut donner des informations détaillées sur les effets dynamiques de composants subordonnés et facilite la mesure de la performance pour déterminer les lois de contrôle efficaces et une combinaison de groupe motopropulseur optimale [57, 59, 58, 60, 61, 62]. La simulation dynamique comme les approches de Représentation Energétique Macroscopique (REM) [63, 64, 65], PSIM [66], et V-Elph [60] logiciels de simulation sont développés en utilisant cette méthode.

Stratégie de contrôle

Une stratégie de commande est habituellement mise en œuvre dans le contrôleur central du véhicule, elle est défini comme un algorithme, une loi qui régit le fonctionnement du motopropulseur du véhicule. En général, il saisit les mesures des conditions de fonctionnement du véhicule tels que la vitesse ou l'accélération, le couple demandé par le conducteur, le type de la route actuelle ou des informations de trafic, des solutions d'avance, et même les informations fournies par le Global Positioning System (GPS) [3].

Les principaux objectifs de la gestion de l'énergie du système hybride est de répondre à la demande des pilotes pour la puissance de traction, le maintien de la charge de la batterie, le moins d'allumages, diminuer les coûts de fonctionnement, et l'optimisation de l'efficacité du groupe motopropulseur [50]. Une bonne stratégie de contrôle doit satisfaire un compromis entre eux.

Une stratégie de contrôle peut intégrer des approches pour aider dans le processus de décision. L'approche stochastique peut fournir une situation aléatoire mais prévisible. Elle utilise les données de profil répétée de route s'il n'y a pas de futur profil de conduite [68]. Les outils de reconnaissance peuvent aider à classer les modes de conduite en se basant sur la reconnaissance du comportement de conduite du conducteur fondée sur la condition actuelle et précédente, le modèle d'apprentissage, et la classification appropriée [4, 69]. La prédiction d'événements futurs peut informer et fournir des données de conditions de conduite futures et profil de la route, de prévoir la demande d'énergie et de déterminer la décision de la stratégie de contrôle. L'approche dynamique de commande de rétroaction est facile à mettre en œuvre car elle est basé sur l'opération en cours et précédente [4].

R. Wang and S. M. Lukic [69] résument les outils de prévision qui ont été mis en œuvre sur les systèmes de véhicules électriques et hybrides. Trois techniques sont discutés pour la stratégie de contrôle de prédire le cycle de conduite comme prédiction basée sur GPS [18, 70, 71, 44, 72, 73], Geographical Information Systems (GIS) [44] et Intelligent Transportation Systems (ITS) [4], reconnaissance basée sur la statistique et de l'analyse de cluster, et la commande prédictive basée sur Markov chain [43, 74, 75, 76].

La prédiction basée combiné sur GPS et ITS peut réduire l'incertitude. Le GPS acquiert les informations de conduite présente comme le temps, la vitesse, la distance parcourue, la pente, l'accélération et la décélération. Et les ITS fournissent les conditions routières, les limites de vitesse et les placements de feux de circulation. La statistique et l'analyse de cluster utilisent des données historiques pour reconnaître les types de cycle de conduite (urbain, suburbain ou autoroute) pour mesurer la demande de puissance. La longueur et la fenêtre de temps sont imposées pour collecter et traiter les données compte tenu de la charge de calcul et la facilité de mise en œuvre en temps réel. Pour analyser les données, nous pouvons utiliser les algorithmes de classification comme l'algorithme de classification de bayésien, l'arbre de décision, la théorie des ensembles rugueux, l'analyse de la concentration floue [15, 77], neural network (NN) [78], et le support de la machine de vecteur. Le NN est d'abord formé en utilisant des cycles de conduite connus pour reconnaître les conditions de conduite actuelle et prévoir les événements futurs proches. La chaîne de Markov modélise la demande de puissance et prédit les conditions de conduite d'avenir, compte tenu de l'actuel.

Trois types de style de conduite sont définit : doux, normal, et conduite agressive. Les méthodes de classification et de reconnaissance pourraient être un ensemble de questionnaire, classification floue, l'analyse jerk en utilisant une plate-forme de simulateur de conduite, ou d'un des modèles de mélange gaussien. Des études montrent qu'un conducteur agressif contribue à moins d'économie de carburant et proposent d'allouer moins de demande de couple pour éviter la consommation de carburant en raison de fonctionnement transitoire du moteur. Il existe diverses méthodes et approches pour déterminer la décision d'un contrôleur. Deux méthodes principales sont la stratégie de contrôle à base de règles et de la méthode d'optimisation.

Méthode basée sur les règles

La stratégie de contrôle à base de règles est basée sur l'intuition de l'ingénierie et la simple analyse des tableaux de rendement des composants [42]. Elle est facile à mettre en œuvre [4] et efficace en temps réel pour le contrôle de surveillance du flux de puissance d'un VHE [3, 16].

Les systèmes fonctionnent et reposent sur un ensemble de critères définis. L'objectif est de faire fonctionner le système à son plus haut point de rendement [21].

Les règles prédéfinies sont initialement configurés en fonction des sorties désirables et les attentes sans aucune connaissance préalable du voyage. Des organigrammes et des diagrammes d'états sont couramment utilisés pour représenter le flux de puissance d'un schéma de conduite donnée. Les stratégies de contrôle à base de règles optimisent les performances de chaque composant individuellement. Cependant, c'est une optimisation locale qui présente un inconvénient majeur de ne pas être en mesure de trouver le minimum global [21]. La mise en œuvre est réalisée avec la méthode fondée sur la règle déterministe ou la méthode fondée sur la règle floue.

Méthode d'optimisation

Les méthodes de contrôle à base d'optimisation peuvent être en temps réel, global, local, l'optimisation de paramètre ou de seuil. Elles peuvent fournir une généralité et réduire le réglage lourd des paramètres de contrôle [48]. Les contrôleurs basés sur cette optimisation ont la tâche principale de minimiser une fonction de coût. Cette fonction de coût est calculée en fonction des paramètres des véhicules, des composants et les attentes de rendement du véhicule [21]. L'optimisation de système global prend en compte l'efficacité de tous les appareils et détermine la distribution de puissance de chaque système [25]. Normalement, l'intention de ces stratégies de contrôle est de maximiser l'efficacité de la chaîne cinématique tout en minimisant les pertes [16]. L'optimisation offre également la possibilité d'intégrer deux variables, les objectifs de kilométrage et d'émission, comme une fonction de coût qui peut être optimisée [21]. Les couples de référence optimaux pour les convertisseurs de puissance et les rapports de transmission optimaux peuvent être calculées par minimisation d'une fonction de coût qui représente généralement la consommation de carburant ou les émissions [3, 16]. Les conditions d'information sur le voyage et les composants précis sont essentiels dans le développement d'un contrôleur optimal. Les progrès technologiques tels que les GPS, les cartes et des données de trafic en temps réel ont simplifiés les méthodes [21].

Conclusion

Il existe beaucoup de méthodes qui peuvent être appliquées comme stratégie de contrôle en fonction de son utilisation. En conclusion générale, nous pouvons affirmer que le facteur énergétique a accélérer le développement de véhicules électriques et hybrides. La plupart des objectifs traités dans les recherches effectuées sont liées à l'économie de carburant. Ensuite, vient la préoccupation environnementale et du facteur d'émission dans le but de réduire les gaz carboniques et de particules émis par le moteur. Au niveau du système, les motifs sont de parvenir à baisser le coût d'exploitation, avoir une efficacité optimale de motopropulseur, et de répondre à la demande de puissance de traction. La bonne conduite et les transitions en douceur ont été au centre de recherche des systèmes de transmission pour véhicules hybrides. L'état de charge ou la santé des batteries deviennet l'un des éléments importants pris en compte dans la gestion de l'énergie dans un système de véhicule équipé d'une capacité de batterie relativement plus importante.

La conception du contrôleur est différente pour chaque système, cela dépend de l'architecture, de l'utilisation, du degré d'hybridation, et les objectifs ciblés. Comme nous pouvons l'observer, un véhicule hybride en série et un véhicule hybride pile à combustible/batterie ont besoin d'un contrôleur pour gérer la distribution de la puissance entre ses sources d'énergie sous forme d'énergie électrique. Contrairement à un hybride parallèle et un hybride série-parallèle, le contrôle est limité pour déterminer sa répartition du couple sous forme d'énergie mécanique pour fournir la puissance demandée aux roues.

Une bonne commande fournit une solution optimale, peut être utilisé dans un véhicule réel, a une bonne stabilité et sensibilité, peut fournir la puissance demandée, et peut améliorer l'efficacité du système. Les recherches effectuées présentent le développement nécessaire dans les stratégies de contrôle en raison de l'avance technologique.

La méthode basée sur des règles est facile à mettre en œuvre et est robuste, mais elle n'est pas facile dans ses réglages des paramètres de contrôle. Dans la plupart des cas, la simulation est réalisée hors ligne pour déterminer les seuils des paramètres optimaux à appliquer dans le véhicule réel. Cela peut être fait en utilisant des cycles standard disponibles ou des informations de voyage passé. Une bonne modélisation du système du véhicule peut représenter le comportement et l'interaction entre les sous-systèmes. Dans la méthode d'optimisation globale, le cycle complet voyage ou de conduite doit être connue a priori pour atteindre une solution optimale. Même si ce n'est pas approprié pour une application dans le monde réel, elle peut être utilisée pour optimiser les paramètres ou les règles pour les autres stratégies de contrôle, ou de comparer la performance d'une stratégie de contrôle en développement.

Modélisation vers un modèle efficace pour VHE série

Introduction

Un véhicule électrique hybride (VHE) est considéré comme une solution efficace au problème de la pénurie d'énergie et les exigences pour accroître l'efficacité des combustibles fossiles. Le système a des avantages tels que l'économie de carburant et la réduction des émissions de polluantes, une efficacité de carburant plus élevée et de meilleures performances qu'un véhicule classique [15, 14]. La présence d'un système de stockage d'énergie réversible (ESS) offre de nouveaux degrés de liberté pour fournir la puissance, la possibilité de réduction de la cylindrée, la marche au hors ralenti, de freinage récupératif, et de pouvoir aider la propulsion qui peuvent augmenter l'efficacité globale du système [8, 7].

La conception de l'architecture du système de VHE est complexe, et la gestion de l'alimentation est compliquée en raison d'un haut degré de flexibilité de contrôle, ainsi que l'utilisation de composants non-linéaires et multi-domaine. La détermination des paramètres de conception et de coordination des sources et des multiples convertisseurs d'énergie afin d'optimiser pleinement son potentiel est fastidieux, lent et coûteux [58, 8, 10, 62, 64, 65]. La modélisation de configurations de VHE et les interactions entre ses composants devient indispensable pour le prototypage et l'analyse rapide des VHE.

La technologie VHE a été développée pour de nombreuses applications et différentes combinaisons de conception comme série, parallèle et série-parallèle. La configuration hybride série est le type le plus simple du VHE et prédomine dans le transport urbain grâce à sa performance et sa réponse de la puissance transitoire exceptionnelle [14, 66, 15]. Le faible niveau de bruit en raison de l'utilisation de moteurs électriques seuls pour la traction offre des avantages en particulier dans les opérations militaires, mais plus grand système d'entraînement et les conversions énergétiques multiples contrecarrer l'efficacité globale de cette architecture [80].

Des modèles de systèmes VHE ont été développées pour diverses applications couvrant des sujets tels que les problèmes de conception optimales [60, 40, 62], interactions sous-systèmes

[40, 53], le développement de contrôleurs [58, 50, 98, 23, 80, 17], et la maniabilité du système [56]. Même si les modèles qui peuvent représenter avec précision une série VHE système existent, un développement du modèle de ce système qui se concentre sur une voiture de compétition n'est pas encore disponible.

Deux méthodes de modélisation seront utilisées pour modéliser une voiture de course hybride appelé *Noao*. Les résultats de test du système de vraie voiture de course sur le circuit seront utilisés pour valider les modèles. Tout d'abord, un modèle quasi-statique est développé pour valider les paramètres et les rendements du système étudié, qui sera également utilisé pour l'optimisation de la stratégie de contrôle du système.

Et puis, un développement de ce modèle de voiture en utilisant la méthode dynamique sera nécessaire pour évaluer la performance de la voiture et de générer son cycle de conduite en fonction de l'entrée du conducteur. En outre, ce type de modèle sera la plate-forme pour évaluer les améliorations dues à des changements qui seront effectués à ce système, et de tester une nouvelle stratégie de contrôle optimale approprié pour ce système.

Voiture NOAO

La voiture *Noao* est un plug-in série voiture de course hybride (Figure 7.3) équipé d'un MCI/génératrice (E/G) défini comme prolongateur d'autonomie. Cette voiture est le résultat d'un travail collectif par des experts et des spécialistes de voiture de course autour de site industriel circuit de Magny-Cours pour l'application de la compétition de la piste de course [99, 100], où il devient une référence pour les recherches en cours sur le système de VHE.

L'Association des Entreprises Pôle de la Performance de Nevers Magny-Cours et Magny-Cours Circuit utilisent leur expertise et leurs expériences pour construire la voiture indiqué dans Figure 7.2 et de définir son algorithme de commande heuristiquement.

L'architecture du véhicule est présenté dans Figure 7.3 avec la direction des flèches correspondent aux flux de puissance dans le système. Le groupe motopropulseur est composé d'un moteur électrique de traction (EM), un convertisseur de puissance (PC), une batterie (B), et un ensemble de prolongateur d'autonomie constitué d'un moteur à combustion interne (ICE) et une génératrice (G) .

Les paramètres des composants du véhicule sont représentées en table 7.1. Les caractéristiques de cette voiture peut être trouvé dans le site de l'association [99]. Le moteur électrique est une machine synchrone à aimant permanent, agit comme moteur lors de la traction et comme génératrice durant le freinage régénératif. Le moteur à combustion interne est un moteur à essence avec un 998 cm^3 volume de déplacement.

Trois batteries identiques sont utilisés comme système de stockage d'énergie réversible (ESS), fournissent la plupart de l'énergie nécessaire à la propulsion et récupérer de l'énergie lors du freinage régénératif. Le MCI/générateur (E/G) ensemble génère de l'énergie pour la partie prolongateur d'autonomie. Les deux sources d'énergie sont connectés à un bus d'alimentation électrique qui est relié au convertisseur d'alimentation du moteur électrique.

Figure 7.2: Voiture de course NOAO.

Actuel stratégie de contrôle

La méthode de gestion de l'énergie utilisée dans la voiture originale est une stratégie de contrôle à base de règles, choisi en raison de sa simplicité et sa grande utilisation dans les véhicules de démonstration. C'est une méthode heuristique et la détermination de ses seuils de paramètres sont basés sur l'observation de la puissance demandée.

Basé sur une documentation de la commande de prolongateur d'autonomie [101], trois sous-systèmes de contrôle sont définis pour contrôler la partie prolongateur d'autonomie; la commande de mode, le contrôle de séquence, et le contrôle de la vitesse grâce à l'application D-Space.

La commande de mode gère le mode de l'entraînement, de la course, ou de la feu-up qui

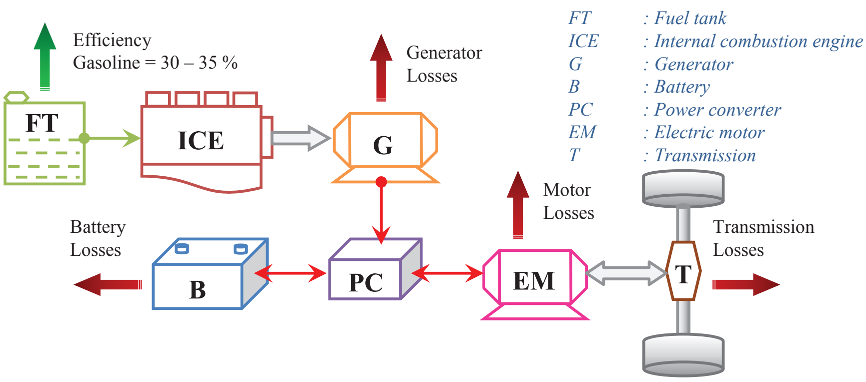


Figure 7.3: Architecture de l'hybride série.

Table 7.1: Paramètres de NOAO

Masse véhicule , m_v	1200 kg
Surface frontale, A	2 m^2
Coefficient de traînée, C_x	0.35
Résistance au roulement, μ	0.012
Diametre de la roue, d_w	0.62 m
Moteur à combustion interne	3 cylindres 1.0 L, injection directe
Génératrice	54 kW at 4500 tr/min, 120 Nm
Moteur électrique	280 kW puissance maximale, 800 Nm
Batterie	3 Lithium-ion batteries, 520 V
Transmission	Simple, ratio 2.9, rendement 0.95

définit les conditions pour permettre l'allumage de la prolongateur d'autonomie. Ce contrôle du sous-système prend la vitesse de la voiture, la puissance de traction, SOC, et quinze autres paramètres liés à la température et courant comme entrées pour produire de la puissance ciblée.

Les sorties sont alors évalués pour définir cinq états de la séquence de contrôle; éteindre, démarrage, rampe montée, charge, et rampe descente pour déterminer la masse de carburant à injecter dans le moteur pour produire le couple nécessaire à la fois à la MCI et la génératrice.

Ensuite, en utilisant un régulateur PI à action directe, la commande de vitesse détermine le couple requis en fonction de la consigne de vitesse définie par la commande de séquence.

Comme dans son système réel, des paramètres similaires tels que la puissance de traction nécessaire à la roue et le SOC de la batterie seront prises comme entrées du prolongateur d'autonomie pour les simulations de ce système de voiture.

Modèle quasi-statique

Un modèle de quasi-statique est un modèle non causale, où ses entrées et sorties ne sont pas fixes. Ce genre de modèle se compose d'un modèle à l'état constant à laquelle un modèle dynamique équivalente du système est ajouté [54]. Comme dans un moteur, il associe une carte et un premier ordre du système pour former ce modèle.

Dans cette étude, il est utilisé pour déterminer les caractéristiques et les paramètres des composants de systèmes. Ceci est réalisé en comparant les résultats des expériences et de la simulation de chaque composants. Ce modèle est utile dans une solution numérique qui a un lourd charge de calcul, car il utilise un pas de temps plus grand et plus lent pour la modélisation.

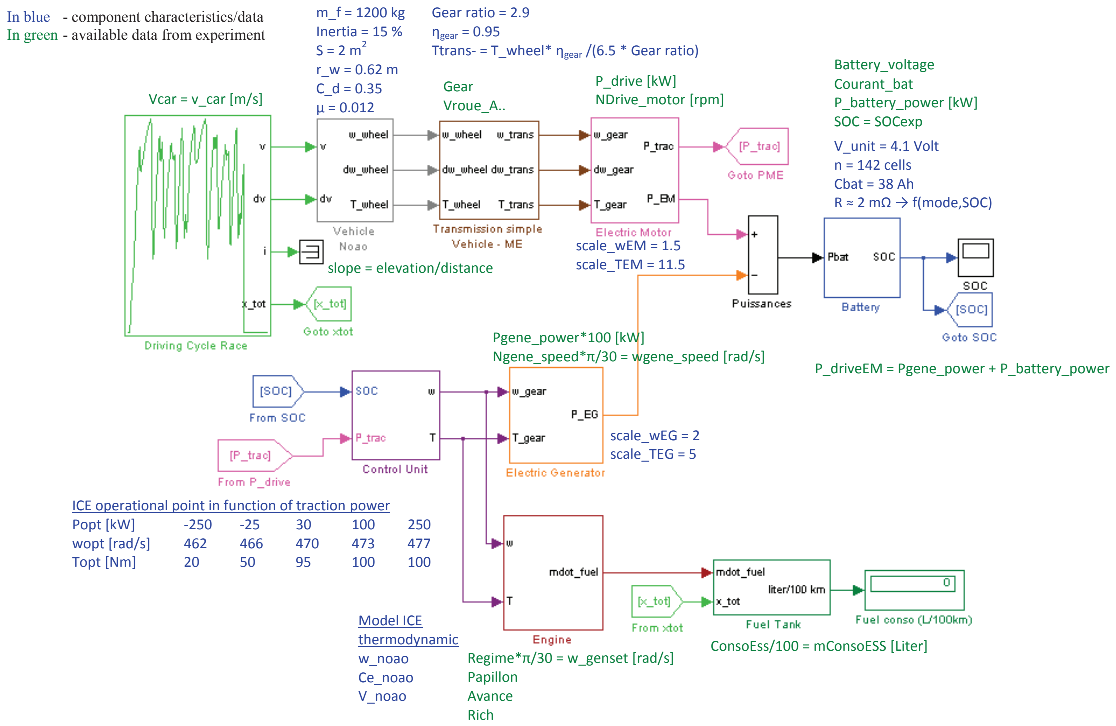


Figure 7.4: Modélisation de la voiture NOAO utilisant la méthode de modélisation quasi-statique.

Comme on peut le voir sur Figure 7.4, la puissance demandée est obtenu à partir du cycle de conduite. C'est une méthode de simulation vers l'arrière [54], de la vitesse du véhicule, au moteur et puis à la batterie pour calculer la consommation d'énergie du système. Le modèle est simple et facile à construire, mais il ne représente pas exactement le comportement du système comme dans son système réel.

Modèle dynamique

Les modèles dynamiques tiennent en compte des états transitoires dans un contrôle des flux de puissance en temps réel. Une gestion de l'énergie locale doit être assurée en temps réel, il est donc essentiel de comprendre la fonction de chaque sous-systèmes en fonction de la causalité physique comme dans un modèle causal pour prévenir les risques de dommages et de fonctionnement inefficace.

Un modèle causal utilise le principe de cause à effet pour décrire le comportement du système. Dans certains appareils, il possède une sortie fixe qui est une fonction intégrale de l'entrée avec un temps de retard induit. Il existe de nombreux formalismes graphiques qui peuvent être utilisés pour représenter un système multiphysique et complexe tels que Bond Graphs, Power

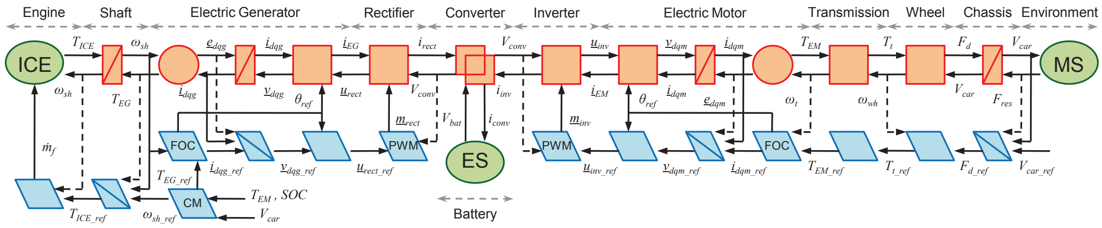


Figure 7.5: Représentation énergétique macroscopique du système de voiture et de son système de contrôle.

Oriented Graphs, Power Flow Diagrams, Causal Ordering Graphs, et Energetic Macroscopic Representation.

Représentation énergétique macroscopique (REM)

La représentation énergétique macroscopique (REM) est une approche de causalité pour la simulation dynamique, dans le but de développer des structures de contrôle basée sur la séparation des systèmes complexes en sous-blocs. Cette méthodologie a déjà été utilisé avec succès pour l'applications des machines multiples [107], systèmes de piles à combustible [108], mais aussi la traction électrique du véhicule [63, 64, 65, 109, 110].

L'architecture globale du modèle REM y compris tous les composants et les blocs de commande pour la voiture de course hybride série *Noao* est présentée dans Figure 7.6. Les blocs ovales vert sont la source d'énergie, blocs orange sont les convertisseurs et les blocs bleus sont les blocs de contrôle. Un bloc ayant une croosbar est un élément à accumulation d'énergie et le bloc doublé est un dispositif de couplage [63, 65, 64, 111]. Un convertisseur de domaine monophysical est carré et un convertisseur de domaine multiphysique est ronde. Le synoptique récente du REM est inclus dans [112].

REM de cette voiture est basée sur la représentation faite en [110] où la batterie et le convertisseur de courant sont combinés pour former la source électrique équivalente (ES_{eq}) pour la partie de traction du système. Avant cela, la représentation appropriée est comme dans Figure 7.5.

Controlê sur la base d'inversion

L'objectif de REM est de fournir une méthode simple pour élaborer une stratégie de commande sur la base d'inversion pour les systèmes complexes et multi-physiques. La structure de commande est développé par une inversion du bloc du modèle, où des blocs intégrale et les blocs de connexion nécessitent le plus d'attention [107, 64, 111].

Par cette méthode, chacun des éléments de REM de la chaîne de réglage sont inversées pour déduire la chaîne de contrôle [110, 63]. Les blocs convertisseurs tels que la transmission peut être

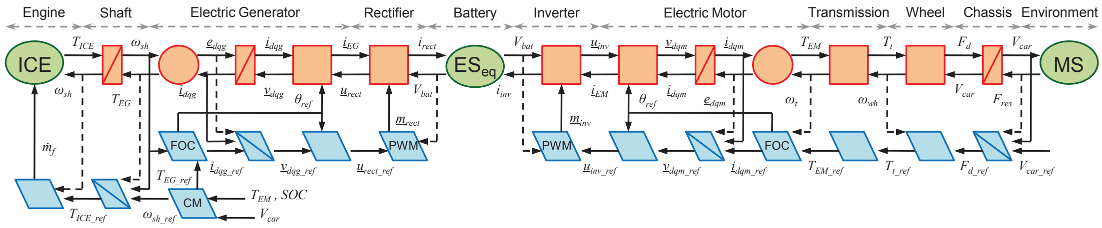


Figure 7.6: Représentation énergétique macroscopique du système de voiture et de son système de contrôle à la source électrique équivalent.

simplement inversées, mais une entrée de critère est nécessaire pour l'inversion des dispositifs de couplage [109].

Conclusion

Un système complet de voiture de course hybride série est modélisée en utilisant REM. La comparaison avec la simulation et les résultats expérimentaux montrent que le système est correctement représenté en ce qui concerne le moteur électrique de traction, le système de batterie, le moteur à combustion interne et la génératrice électrique, crée un outil précieux pour le développement de ce système. En outre, le modèle peut être utilisé comme base pour développer une meilleure stratégie de contrôle de ce système en utilisant les approches basées sur des règles ainsi que des approches d'optimisation. Des diverses améliorations peuvent être étudiés et effectué en utilisant cette méthode et le modèle, comme une optimisation de points de travail de MCI pour réduire la consommation ou les émissions dangereuses, une amélioration des paramètres de conception, ou de concevoir un meilleur système de gestion de la batterie ou les machines électriques.

Ce modèle est ensuite utilisé pour développer ce système pour une nouvelle architecture aves les piles à combustible comme son prolongateur d'autonomie. Trois cycles de course d'entraînement sont utilisés pour tester le potentiel de l'intégration de la pile à combustible. Il peut être conclu que la même quantité d'énergie demandée au prolongateur d'autonomie, une voiture de course hybride à pile à combustible/de la batterie est plus efficace que la voiture électrique hybride utilisant un prolongateur d'autonomie MCI/génératice. En raison de sa plus grande efficacité, la pile à combustible fournit une autonomie plus longue pour la puissance maximale de moteur équivalent. La possibilité d'améliorer l'IMC de 38 à 69 pouvant être obtenu par le véhicule en raison d'une meilleure efficacité est montrée. Mais, pour éviter le surdimensionnement et d'avoir un coût et le poids opérationnel inférieur, un système de pile à combustible de 40 kW puissance nominale va répondre aux exigences à l'égard de cette demande de voiture de course spécifique. Bien que les résultats obtenus ne sont pas encore précis, ce modèle et approche de déduire le système de contrôle peut être utilisé à la première étape de la conception et le dimensionnement des composants de la pile à combustible dans le système.

Stratégie de contrôle optimale et adaptive pour une voiture hybride série de course

Introduction

Dans le chapitre précédent, les modèles de systèmes du véhicule sont validés avec les résultats de l'expérience et certaines améliorations peuvent être effectué au système de la voiture pour obtenir une meilleure efficacité. Dans ce chapitre, les optimisations seront effectuées sur la stratégie de contrôle pour mieux gérer les énergies disponibles pour le système.

La stratégie de contrôle pour les systèmes du VHE peut être la méthode basée sur le règle ou la méthode d'optimisation. La stratégie basée sur le règle (RB) est faite sur l'intuition de l'ingénierie et analyse simple sur les tables de rendement des composants ou des tableaux [42, 138, 68]. Il est robuste et a moins de charge de calcul [23, 15, 3, 4, 16]. La stratégie de contrôle de la RB est facile à mettre en œuvre pour un contrôle de surveillance en temps réel du flux de puissance dans un véhicule hybride [8, 68, 23, 15, 4]. Il peut atteindre de près de la solution optimale, mais ne peut pas être facilement mis en œuvre à un autre cycle de la conduite ou véhicule en raison du manque d'optimisation formelle et la généralisation, donc ne peuvent pas exploiter pleinement le potentiel de l'architecture de VHE [23, 4, 7, 21].

Les méthodes de contrôle à base d'optimisation peuvent être locales, global, en temps réel, l'optimisation de paramètre ou de seuil. La méthode d'optimisation peut fournir généralité et de réduire un tuning lourde des paramètres de contrôle [48]. Sa tâche est de minimiser une coût fonction en temps réel ou en déconnecté sur la base des paramètres de véhicules et de composants, ainsi que les attentes de rendement du véhicule [21].

Dans ce travail, la méthode d'optimisation DP est choisie pour optimiser la stratégie de contrôle pour cette voiture NOAO. Cette méthode a été largement utilisée pour optimiser la gestion énergétique des véhicules hybrides, et cette fois il sera utilisée pour optimiser la stratégie de contrôle d'un système de véhicule de type de course. La différence est le cycle de conduite, il est obtenu à partir d'expériences menées sur le circuit de Magny-Cours en France. Une optimisation globale peut être fait parce que une information spécifique et précise de tous les composants est disponible. DP est choisi sur les autres approches parce qu'elle a établi une réputation comme la référence d'autres stratégies de contrôle avec sa solution optimum global [8, 4, 4]. L'un des intérêts de cette étude est de savoir comment mettre en œuvre cette approche hors ligne puis de l'adapter pour une application en temps réel afin d'optimiser la répartition de puissance du système en utilisant un cycle de conduite prévu.

Analyse sur la stratégie de contrôle actuelle

Pour cette voiture NOAO, le but de contrôle est d'épuiser l'état de charge (SOC) de la batterie de son SOC initial plein au début de la course et d'atteindre une limite basse de la SOC finale après un certain nombre de tours à la fin d'un course.

Une méthode de contrôle appropriée pour un plug-in VHE est un appauvrissement de la charge de la batterie de sa limite supérieure à sa limite inférieure à travers un cycle de conduite pour atteindre la meilleure efficacité [4]. Pour une voiture de compétition de piste, le cycle de conduite sera le cycle de conduite sur un circuit après un certain nombre de tours. La stratégie de contrôle de cette voiture consiste à mettre toujours le moteur en mode d'aider la propulsion de la voiture pendant les courses pour plus d'autonomie.

Du chapitre précédent, on peut observer à partir de l'architecture du véhicule dans figref fig: Archi, la génératrice transforme l'énergie mécanique du moteur à l'électricité pour recharger la batterie ou d'aider le moteur pour la propulsion. Le couple de charge de traction ne concerne que le couple du moteur électrique, donc l'ensemble E/G peut fonctionner à ses points de travail optimales à tout moment.

En outre, le contrôleur de la prolongateur d'autonomie comprend trois sous-systèmes pour déterminer la vitesse de rotation et la référence de couple. Peut-être, un sous-système peut être ajouté au contrôleur qui sera un élément de prédiction pour déterminer les meilleurs seuils pour chaque type de cycle de conduite pour ce système de voiture.

Conclusion

Une méthode d'optimisation DP est appliquée sur NOAO, une voiture de course hybride série avec un prolongateur d'autonomie de MCI. En utilisant DP, les résultats de la simulation montrent l'amélioration possible de la consommation de carburant et le rendement du système pour le même cycle de conduite et de lépuisement SOC du résultat expérimental de la vraie voiture. La même approche de la DP est utilisée pour étudier la possibilité d'augmenter l'autonomie de la voiture de course et prouvé pour être réalisable. Ces résultats sont ensuite analysés et seront utilisées pour ajuster les paramètres de commande de la génération de puissance MCI/génératrice. Ensuite, l'approche DP est mis en œuvre à un cycle de conduite plus agressive appliquée pour le même circuit de course. Mais la voiture dispose d'une autonomie plus courte sous cette condition. Comme perspectives, cette approche d'optimisation globale sera étudiée plus pour être utilisés dans l'application de contrôle réel de voiture de course. Cette approche peut diviser la puissance de façon optimale que dans certains practice en fonction de cycles de conduite.

Ensuite, un modèle dynamique REM est développé pour prévoir des cycles de conduite de ce système de voiture de course hybride série et de tester l'adaptation des seuils optimisés pour une application en temps réel. Un modèle dynamique de la roue unique du véhicule est utilisé pour la simulation et il montre une précision acceptable avec la voiture de course réel sur les circuits de course étudiés. Comparaison entre la stratégie de contrôle actuelle à base de règles, l'optimisation DP fait pour cette voiture, et un modèle mis au point avec des seuils de contrôle ajustés en fonction des résultats de l'optimisation DP montre une amélioration sur l'efficacité du système par rapport à sa stratégie de contrôle actuelle de répartition de la puissance. Pour le même profil et la performance de vitesse, la voiture avec la commande ajusté peut obtenir plus d'autonomie sur une déplétion SOC prévue.

Une analyse sur lénchantillon de pédale sur les zones particulières en fonction de sa distance est présenté pour deux circuits de course différentes et sera utiliser comme une méthode de prédiction de prévoir les actions de pilotes sur le pédale sur d'autres pistes de course. Cette méthode est utile pour obtenir le profil de vitesse et le profil de puissance de la voiture pour les limites de puissance déterminés et créer une multitude de cycles de conduite pour son optimisation en termes de consommation de carburant, l'efficacité du système, le temps de conduite, ou SOC trajectoire. Dans l'avenir, le modèle peut également être utilisé pour redéterminer les paramètres des composants automobiles pour une meilleure performance ou practice. En dehors de l'application de voiture de course, cette méthode peut être étendue à prévoir les cycles de bus ou véhicules de bureau de poste où les contraintes de conduite seront similaires; le style de conduite agressif, un trajet prèsque fixe, et avoir peu de temps pour terminer le circuit. La mise en œuvre sera différent selon le type de véhicule, mais les concepts d'utilisation d'entrée sera le même pour prédire le cycle de conduite et l'utilisation de l'énergie.

Points de fonctionnement du MCI dans VHE applications

Introduction

Dans le chapitre précédent, la méthode consiste à l'élaboration du modèle de système et sa vérification avec les résultats de l'expérience ont été discutés. Grâce à ce chapitre, ce modèle est ensuite utilisé pour simuler quatre stratégies de contrôle qui ont été largement utilisés pour l'architecture du système dont les résultats seront ensuite analysés pour l'amélioration de la MCI comme indiqué dans Figure 7.7.

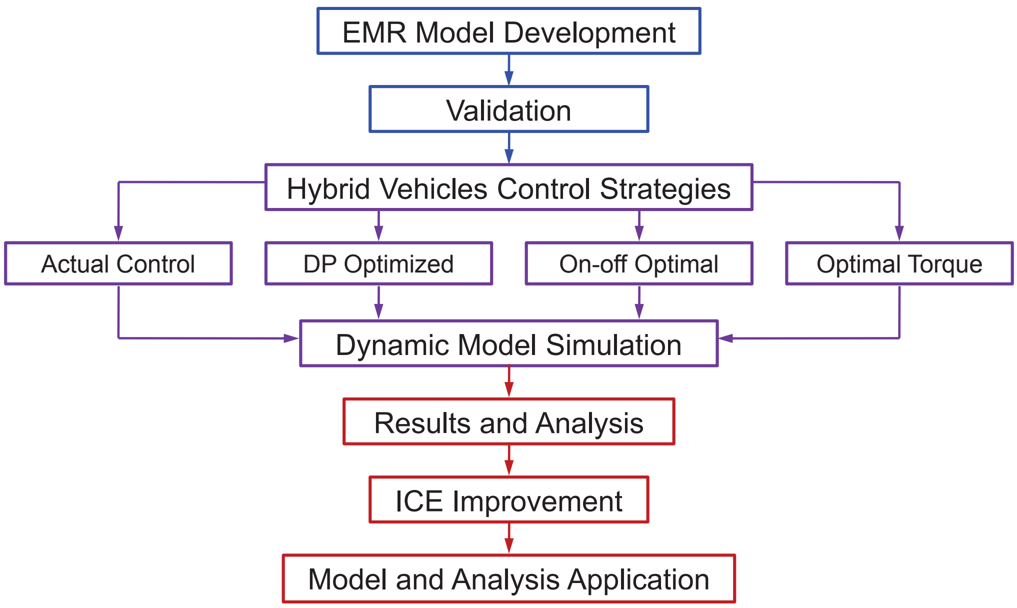


Figure 7.7: Procédé de l'analyse.

Dans les articles publiés, ils discutent et proposent une méthode pour contrôler le système de véhicule hybride et d'évaluer sa consommation, émissions, et sa mise en œuvre. Dans ce chapitre, les méthodes de gestion de l'énergie les plus utilisés et proposés qui ont été prouvées efficaces et applicables pour ce système sont testés par simulation et sont analysés plus en détail. L'analyse interprète la consommation de la combustible et le temps usé à des points spécifiques du moteur en termes de pourcentage, car il est plus représentatif pour chaque cycles de conduite. Objectifs de cette analyse sont les suivants:

- Pour identifier la meilleure stratégie optimale et de commande approprié pour ce système et son application.
- Pour analyser l'effet de la stratégie de contrôle différent sur la façon des sources d'énergie consommées.
- Pour pondérer la consommation à chacun des points opérationnels dans le moteur utilisé pour cette architecture de système.
- Pour déterminer la plage de vitesse et de charge qui peut être optimisée comme des mesures pour améliorer l'économie de carburant pour un système hybride.
- Pour définir le temps passé sur chacun des points operational du moteur afin d'évaluer et de réduire les émissions de gaz à effet de serre.
- Pour mesurer les réductions possibles qui peuvent être réalisées en améliorant notamment les points de fonctionnement du moteur.

Cette méthode d'analyse n'ont pas été menées avant parce que la motivation de développement de ce système est principalement axée sur la gestion optimale de l'énergie. Il est également besoin beaucoup du temps et des ressources pour faire une réelle expérimentation. Au moment où ce modèle est développé il ya toujours un manque d'un modèle de simulation dynamique complet qui peut représenter le système près de la véritable véhicule hybride.

Remplacement par un véhicule entièrement électrique est encore longue et coûteuse pour les secteurs entiers des transports. Au lieu d'éliminer l'utilisation du moteur, l'optimisation de son utilisation peut économiser du carburant et réduire les émissions. Un de l'alternative possible est en identifiant et en mesurant l'opération de moteur le plus récurrent dans ce système qui peut donner le plus grand conséquence après l'amélioration.

Conclusion

Dans ce chapitre, quatre stratégies de contrôle largement utilisé pour les systèmes de VHE ont été identifiées et testées sur un modèle dynamique qui ont été développés dans le chapitre précédent. Les stratégies de contrôle sont; l'actuel stratégie de contrôle, la stratégie de contrôle de DP optimisé, la stratégie de contrôle du point optimale, et la stratégie de contrôle de couple optimale.

Les cycles de conduite de course et de conduite de route sont les deux types de cycles étudiés dans l'analyse des points de fonctionnement du MCI dans un VHE. Il analyse les différentes façons de contrôler le système et comment une énergie du système est consommée afin d'identifier la stratégie de contrôle le plus approprié pour chaque application et de définir ses améliorations possibles.

L'analyse consiste à déterminer la quantité de carburant à une zone particulière et pondéré son impact pour i'améliorations du moteur. Le temps passé à un des points particuliers sont également quantifié pour identifier la zone de points de travail récurrentes qui seront utiles pour réduire les émissions de gaz à effet de serre.

Ensuite, le modèle et la méthode d'analyse est utilisée pour déterminer un contrôle optimal et le dimensionnement pour une application automobile normale. Cela se fait en réduisant le nombre de cellules de batterie dans la voiture. La limite d'autonomie est un critère pour déterminer le dimensionnement optimal de la batterie.

Si l'on utilise les mêmes paramètres de commande pour déterminer le couple et la vitesse de référence du prolongateur d'autonomie, elle se traduit par les mêmes points de fonctionnement pour un même cycle de conduite même si les cellules de batterie sont réduits. Mais dans ce cas la tension du pack de batterie tombe quand son courant augmente en fonction du nombre de cellules de la batterie diminué.

La méthode d'analyse et la méthode rétrospective sont utiles pour étudier et identifier la stratégie de contrôle la plus appropriée, les modifications à prendre pour l'algorithme de contrôle, le bon dimensionnement des composants du système pour une utilisation particulière, et les améliorations à effectuer sur les zones opérationnelles du MCI qui donneront le plus d'impact après optimisation afin d'obtenir une meilleure efficacité énergétique du système.

Conclusion et perspectives

Dans le premier chapitre, une revue sur les véhicules hybrides, la méthode de modélisation, et ses stratégies de contrôle sont documentés dans cette partie de la thèse. Depuis le premier développement du système VHE, différentes architectures, sources d'énergie, et les stratégies de contrôle ont été développé et testé afin d'améliorer l'efficacité de ce système. Et cela continuera tant que le monde entier est préoccupé par les changements de climat et réchauffement de la planète qui sont maintenant affectent aussi notre vie quotidienne. Avec les nouvelles technologies qui peuvent être utilisées pour prédire les trajets du véhicule et la consommation des énergies, une gestion optimale de l'énergie peut être exécutée facilement.

Après la phase de revue, vient le développement du modèle de véhicule, commencé avec un modèle de quasi-statique, puis un modèle dynamique qui peut bien représenté le comportement réel du système comme dans son système réel. Le modèle dynamique est développé en utilisant la méthode de REM en fonction de la causalité physique du système. Vérification des modèles sont faits en comparant les résultats obtenus dans les expériences et les tests d'entraînement effectuer pour cette voiture de la compétition sur un vrai circuit de course. Dans la première étape, avec la même stratégie de contrôle, l'optimisation est appliquée en changeant le point de fonctionnement moteur et de la génératrice. Ensuite, le modèle est utilisé pour tester l'intégration d'un système de piles à combustible en tant que le prolongateur d'autonomie du système de véhicule hybride qui est encore en niveau d'étude pour construire le système.

Le chapitre suivant est la méthode d'optimisation de la stratégie de contrôle et le développement d'un outil pour prévoir les cycles de la conduite automobile pour une compétition sur les pistes de course. DP est utilisée pour optimiser la stratégie de contrôle effectif du système sur le cycle de conduite connu, obtenue à partir d'expériences de la voiture étudiée. La méthode de prévision de cycle de conduite est déduite des actions du conducteur sur la pédale sur certaine zone d'un circuit. Cette méthode aura besoin du modèle dynamique pour simuler partie par partie afin de égaler la distance parcourue et le temps terminée.

Dans le cinquième chapitre, le modèle est utilisé pour tester et comparer les stratégies de contrôle applicables et réalisables pour le système grâce à la simulation. Analyse des points de fonctionnement du MCI sous différentes stratégies de contrôle et sa tendance à la consommation pour le système étudié sont analysés. Ensuite, une méthode rétrospective de concevoir une même architecture de véhicule, mais pour d'autres applications est étudié. Les avantages de cette méthode est qu'il est fait en utilisant un modèle bien établi comme référence pour concevoir d'autres architectures ou des stratégies de contrôle. Cette méthode d'analyse et de modèle peut être appliqué à concevoir un meilleur système de véhicule hybride en termes de dimensionnement, la stratégie de contrôle, et des composants optimisés.

Comme perspectives, le modèle développé peut être utilisé pour étudier ce système pour des différentes applications de course ou pour développer un système avec d'autres architectures de véhicule hybride. Le MCI peut être optimisée par des experts et des spécialistes du développement des moteurs afin d'obtenir une meilleure efficacité énergétique et de réduction des émissions de gaz à effet de serre.

REM est une bonne méthode pour représenter un modèle dynamique et il peut être utilisé pour modéliser des machines électromécaniques. La mise en œuvre de REM peut être envisagé pour modéliser un autre système qu'un système véhicule, comme un système d'énergie renouvelable, un nouveau système électro-mécanique ou un système robotisé.

Dans les dernières décennies, les moteurs thermiques ont été la source d'alimentation le plus utilisé dans les véhicules en raison de sa compacité c'est-à-dire le rapport poids-puissance et la puissance par rapport au volume. Jusqu'à présent, les moteurs thermiques pour les véhicules conventionnels ont également été optimisé et ont atteindre une meilleure efficacité pour système d'aujourd'hui et son utilisation continuera. Mais, en raison des inquiétudes environnement, la concentration a été accordée au développement des véhicules électriques, mais ce type de système est encore cher et ont un long chemin à être bien adopté par les consommateurs. Peut-être, le système de VHE émergents n'est pas une fin de l'utilisation des moteurs thermique, mais il est juste le début d'une utilisation efficace des moteurs thermiques pour un meilleur avenir de l'environnement s'il est bien collaboré avec d'autres sources d'énergie et convertisseurs de puissance.

Bibliography

[1] B. M. Baumann, G. Washington, B. C. Glenn, and G. Rizzoni, "Mechatronic design and control of hybrid electric vehicles," *IEEE/ASME Journal on Mechatronics*, vol. 5, pp. 58–72, March 2000.

[2] K. T. Chau and Y. S. Wong, "Overview of power management in hybrid electric vehicles," *Energy Conversion and Management*, vol. 43, pp. 1953–1968, October 2002.

[3] F. R. Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," *IEEE Transactions on Vehicular Technology*, vol. 56, pp. 2393–2404, September 2007.

[4] Q. Gong, Y. Li, and Z. R. Peng, "Trip based optimal power management of plug-in hybrid electric vehicles using gas-kinetic traffic flow model," *IEEE Transactions on Vehicular Technology*, vol. 57, pp. 3393–3401, November 2008.

[5] M. Ehsani, Y. Gao, S. E. Gay, and A. Emadi, *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles: Fundamentals, Theory, and Design.* Texas, US: CRC Press, 2004.

[6] A. Sciarretta and L. Guzzella, "Control of hybrid electric vehicles: Optimal energy management strategies," *IEEE Control Systems Magazine*, vol. 27, pp. 60–70, April 2007.

[7] L. Serrao, S. Onori, and G. Rizzoni, "A comparative analysis of energy management strategies for hybrid electric vehicles," *Journal of Dynamic Systems, Measurement, and Control*, vol. 133, May 2011.

[8] C. C. Lin, Z. Filipi, Y. Wang, L. Louca, H. Peng, D. Assanis, and J. Stein, "Integrated, feed-forward hybrid electric vehicle simulation in SIMULINK and its use for power management studies," *SAE Paper*, no. 2001-01-1334, 2001.

[9] B. Geng, J. K. Mills, and D. Sun, "Energy management control of microturbine powered plug-in hybrid electric vehicles using telemetry equivalent consumption minimization strategy," *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 4238–4248, November 2011.

[10] J. Park, Y. Park, and J. H. Park, "Real-time powertrain control strategy for series-parallel hybrid electric vehicles," *SAE Technical Paper Series*, pp. 1–9, August 2007.

[11] D. Grignion, X. Chen, N. C. Kar, and H. Kian, "Estimation of load disturbance torque for DC motor drive systems under robustness and sensitivity consideration," *IEEE Transactions on Industrial Electronics*, vol. 61, pp. 930–942, 2014.

[12] S. S. Williamson, S. G. Wirasingha, and A. Emadi, "Comparative investigation of series and parallel hybrid electric drive trains for heavy-duty transit bus applications," in *Vehicle Power and Propulsion Conference*, pp. 1–10, September 2006.

[13] M. Khan and N. C. Kar, "A bibliography on the development of the design and control technologies for hybrid vehicles," *Journal of International Review on Modelling and Simulations*, April 2009.

[14] J. P. Gao, G. M. G. Zhu, E. G. Strangas, and F. C. Sun, "Equivalent fuel consumption optimal control of a series hybrid electric vehicle," *Journal of Automobile Engineering 2009*, vol. 8, pp. 1003–1018, August 2009.

[15] R. Langari and J. S. Won, "Intelligent energy management agent for a parallel hybrid vehicle-Part I: System architecture and design of the driving situation identification process," *IEEE Transactions on Vehicular Technology*, vol. 54, pp. 925–934, May 2005.

[16] K. C. Bayindir, M. A. Gozukucuk, and A. Teke, "A comprehensive overview of hybrid electric vehicle: Powertrain configurations, powertrain control techniques and electronic control units," *Energy Conversion and Management*, vol. 52, pp. 1305–1313, February 2011.

[17] M. Amiria, M. Esfahanian, M. R. Hairi-Yazdi, and V. Esfahanian, "Minimization of power losses in hybrid electric vehicles in view of the prolonging of battery life," *Journal of Power Sources*, vol. 190, pp. 372–379, February 2009.

[18] C. Quigley and R. McLaughlin, "Using vehicle navigation and journey information for the optimal control of hybrid and electric vehicles," *Advanced Microsystems for Automotive Applications*, pp. 199–211, 2011.

[19] H. Yoo, S. K. Sul, Y. Park, and J. Jeong, "System integration and power-flow management for a series hybrid electric vehicle using supercapacitors and batteries," *IEEE Transactions on Industry Applications*, vol. 44, pp. 108–114, February 2008.

[20] B. Zhang, Z. Chen, C. Mi, and Y. L. Murphey, "Multi-objective parameter optimization of a series hybrid electric vehicle using evolutionary algorithms," in *Vehicle Power and Propulsion Conference*, pp. 921–925, September 2009.

[21] S. G. Wirasingha and A. Emadi, "Classification and review of control strategies for plug-in hybrid electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 111–122, January 2011.

[22] H. D. Lee and S. K. Sul, "Fuzzy-logic-based torque control strategy for parallel-type hybrid electric vehicle," *IEEE Transactions on Industrial Electronics*, vol. 45, pp. 625–632, August 1998.

[23] M. Koot, J. T. B. A. Kessels, B. de Jager, W. P. M. H. Heemels, P. P. J. van-den Bosch, and M. Steinbuch, “Energy management strategies for vehicular electric power systems,” *IEEE Transactions on Vehicular Technology*, vol. 54, pp. 771–782, May 2005.

[24] O. D. Momoh and M. O. Omoigui, “An overview of hybrid electric vehicle technology,” in *Vehicle Power and Propulsion Conference*, pp. 1286–1292, September 2009.

[25] C. E. Nino-Baron, A. R. Tariq, G. Zhu, and E. G. Strangas, “Trajectory optimization for the engine-generator operation of a series hybrid electric vehicle,” *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 2438–2447, July 2011.

[26] V. Sezer, M. Gokasan, and S. Bogosyan, “A novel ECMS and combined cost map approach for high-efficiency series hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 3557–3570, October 2011.

[27] M. Zhang, “HEV powertrain fundamentals,” in *IEEE Transportation Electrification Conference and Expo, ITEC Short Course*, June 2012.

[28] C. Zhang and A. Vahidi, “Route preview in energy management of plug-in hybrid vehicles,” *IEEE Transactions on Control Systems Technology*, vol. 20, pp. 546–553, March 2012.

[29] B. Zhang, C. C. Mi, and M. Zhang, “Charge-depleting control strategies and fuel optimization of blended-mode plug-in hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 1516–1525, May 2011.

[30] A. Rousseau, S. Pagerit, and D. Gao, “Plug-in hybrid electric vehicle control strategy parameter optimisation,” *International Electric Vehicle Symposium*, vol. 23, pp. 1–14, December 2007.

[31] K. T. Chau, Y. S. Wong, and C. C. Chan, “An overview of energy sources for electric vehicles,” *Energy Conversion & Management*, vol. 40, pp. 1021–1029, December 1999.

[32] N. C. Kar, K. L. V. Iyer, A. Labak, X. Lu, C. Lai, A. Balamurali, B. Esteban, and M. Sid-Ahmed, “Courting and sparking: Wooing consumers’ interest in the EV market,” *IEEE Electrification Magazine*, September 2013.

[33] J. Cao, E. Shiju, T. Zhao, X. Zhu, and H. Jiang, “Simulation research on μ synthesis robust control for driving of hybrid-power electric vehicle,” *Advanced Electrical and Electronics Engineering*, vol. 87, pp. 193–200, 2011.

[34] R. Hodkinson and J. Fenton, *Lightweight Electric / Hybrid Vehicle Design.* Jordan Hill, Oxford, UK: Butterworth Heinemann, 1st ed., 2001.

[35] L. Guzella and A. Sciarretta, *Vehicle Propulsion Systems.* Zurich, Switzerland: Springer, 2nd ed., June 2007.

[36] J. Larminie and J. Lowry, *Electric Vehicle Technology Explained.* Oxford, UK: John Wiley and Sons Ltd., 1st ed., 2003.

[37] A. Brahma, Y. Guezennec, and G. Rizzoni, "Optimal energy management in series hybrid electric vehicles," in *American Control Conference*, vol. 1, pp. 60–64, September 2000.

[38] F. G. Harmon, A. A. Frank, and S. S. Joshi, "The control of a parallel hybrid-electric propulsion system for a small unmanned aerial vehicle using a CMAC neural network," *Journal of Neural Network*, vol. 18, pp. 772–780, July 2005.

[39] H. Yoo, B. G. Cho, S. K. Sul, and Y. Park, "A power flow control strategy for optimal fuel efficiency of a variable speed engine-generator based series hybrid electric vehicle," in *Energy Conversion Congress and Exposition*, (San Jose, California), pp. 443–450, September 2009.

[40] G. Rizzoni, L. Guzzella, and B. M. Baumann, "Unified modeling of hybrid electric vehicle drivetrains," *IEEE/ASME Transactions on Mechatronics*, vol. 4, pp. 246–257, September 1999.

[41] S. Kermani, S. Delprat, T. M. Guerra, R. Trigui, and B. Jeannere, "Predictive energy management for hybrid vehicle," *Control Engineering Practice*, vol. 20, pp. 408–420, April 2012.

[42] C. C. Lin, H. Peng, J. W. Grizzle, and J. M. Kang, "Power management strategy for a parallel hybrid electric truck," *IEEE Transactions on Control Systems Technology*, vol. 11, pp. 839–850, November 2003.

[43] C. C. Lin, H. Peng, and J. W. Grizzle, "A stochastic control strategy for hybrid electric vehicles," in *American Control Conference*, vol. 5, pp. 4710–4715, July 2004.

[44] D. V. Ngo, T. Hofman, M. Steinbuch, and A. F. A. Serrarens, "An optimal control-based algorithm for hybrid electric vehicle using preview route information," in *American Control Conference*, (Baltimore, USA), pp. 5818–5823, June-July 2010.

[45] V. H. Johnson, K. B. Wipke, and D. J. Rausen, "HEV control strategy for real-time optimisation of fuel economy and emissions," *SAE Technical Paper*, vol. 1, no. 2000-01-1543, 2000.

[46] S. Stockar, V. Marano, G. Rizzoni, and L. Guzzella, "Optimal control for plug-in hybrid electric vehicle applications," in *American Control Conference*, pp. 5024–5030, July 2010.

[47] S. Stockar, V. Marano, M. Canova, G. Rizzoni, and L. Guzzella, "Energy-optimal control of plug-in hybrid electric vehicles for real-world driving cycles," *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 2949–2962, September 2011.

[48] A. Sciarretta, M. Back, and L. Guzzella, "Optimal control of parallel hybrid electric vehicles," *IEEE Transactions on Control Systems Technology*, vol. 12, pp. 352–363, May 2004.

[49] J. P. Gao, F. C. Sun, H. W. He, G. G. Zhu, and E. G. Strangas, "A comparative study of supervisory control strategies for a series hybrid electric vehicle," pp. 1–7, March 2009.

[50] S. Barsali, M. Ceraolo, and A. Possenti, "Techniques to control the electricity generation in a series hybrid electrical vehicle," *IEEE Transactions on Energy Conversion*, vol. 17, pp. 260–266, June 2002.

[51] S. Barsali, C. Miulli, and A. Possenti, "A control strategy to minimize fuel consumption of series hybrid electric vehicles," in *IEEE Transactions on Energy Conversion*, vol. 19, pp. 187–195, March 2004.

[52] F. Martel, Y. Dubé, L. Boulon, and K. Agbossou, "Hybrid electric vehicle power management strategy including battery lifecycle and degradation model," in *IEEE Vehicle Power and Propulsion Conference*, pp. 1–8, September 2011.

[53] M. Amrhein and P. T. Krein, "Dynamic simulation for analysis of hybrid electric vehicle system and subsystem interactions, including power electronics," *IEEE Transactions on Vehicular Technology*, vol. 54, pp. 825–836, May 2005.

[54] C. C. Chan, A. Bouscayrol, and K. Chen, "Electric, hybrid, and fuel-cell vehicles: Architectures and modeling," *IEEE Transactions on Vehicular Technology*, vol. 59, pp. 589–598, February 2010.

[55] J. A. MacBain, J. J. Conover, and A. D. Brooker, "Full vehicle simulation for series hybrid vehicles," *SAE Technical Paper Series*, June 2003.

[56] D. F. Opila, X. Wang, R. McGee, R. B. Gillespie, J. A. Cook, and J. W. Grizzle, "An energy management controller to optimally trade off fuel economy and drivability for hybrid vehicles," *IEEE Transactions on Control Systems Technology*, no. 99, pp. 1–16, 2011.

[57] B. K. Powell and T. E. Pilutti, "A range extender hybrid electric vehicle dynamic model," in *Proceedings of the 33rd Conference on Decision and Control*, 1994.

[58] B. K. Powell, K. E. Bailey, and S. R. Cikanek, "Dynamic modeling and control of hybrid electric vehicle powertrain systems," *IEEE Control Systems Magazine*, pp. 17 – 33, October 1998.

[59] K. E. Bailey and B. K. Powell, "A hybrid electric vehicle powertrain dynamic model," in *Proceedings of the American Control Conference*, June 1995.

[60] K. L. Butler, M. Ehsani, and P. Kamath, "A matlab-based modeling and simulation package for electric and hybrid electric vehicle design," *IEEE Transactions on Vehicular Technology*, vol. 48, pp. 1770–1778, November 1999.

[61] O. Tremblay, L.-A. Dessaint, and A.-I. Dekkiche, "A generic battery model for the dynamic simulation of hybrid electric vehicles," pp. 284–289, 2007.

[62] D. W. Gao, C. Mi, and A. Emadi, "Modeling and simulation of electric and hybrid vehicles," *Proceedings of the IEEE*, vol. 95, pp. 729–745, April 2007.

[63] K. Chen, A. Bouscayrol, and W. Lhomme, “Energetic macroscopic representation and inversion based control: Application to an electric vehicle with an electrical differential,” *Journal of Asian Electric Vehicles*, vol. 6, pp. 1097 – 1102, June 2008.

[64] Y. Cheng, K. Chen, C. C. Chan, A. Bouscayrol, and S. Cui, “Global modeling and control strategy simulation,” *IEEE Vehicular Technology Magazine*, pp. 73 – 79, June 2009.

[65] K. Chen, A. Bouscayrol, A. Berthon, P. Delarue, D. Hissel, and R. Trigui, “Global modeling of different vehicles,” *IEEE Vehicular Technology Magazine*, pp. 80 – 89, June 2009.

[66] S. Onoda and A. Emadi, “PSIM-based modeling of automotive power systems: Conventional, electric, and hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 53, pp. 390–400, March 2004.

[67] A. M. Phillips, M. Jankovic, and K. E. Bailey, “Vehicle system controller design for a hybrid electric vehicle,” in *IEEE International Conference on Control Applications*, pp. 297–302, September 2000.

[68] D. Ambühl and L. Guzzella, “Predictive reference signal generator for hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 58, pp. 4730–4740, November 2009.

[69] R. Wang and S. M. Lukic, “Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles,” in *Vehicle Power and Propulsion Conference*, pp. 1–7, September 2011.

[70] C. Musardo, G. Rizzoni, and B. Staccia, “A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management,” in *IEEE Conference on Decision and Control, and the European Control Conference 2005*, pp. 1816–1823, December 2005.

[71] M. H. Hajimiri and F. R. Salmasi, “A fuzzy energy management strategy for series hybrid electric vehicle with predictive control and durability extension of the battery,” in *IEEE Conference on Electric and Hybrid Vehicles*, pp. 1–5, December 2006.

[72] M. Sorrentino, G. Rizzo, and I. Arsie, “Analysis of a rule-based control strategy for onboard energy management of series hybrid vehicles,” *Control Engineering Practice*, vol. 19, pp. 1433–1441, August 2011.

[73] B. Geng, J. K. Mills, and D. Sun, “Predictive control for plug-in microturbine powered hybrid electric vehicles using telemetry information,” in *IEEE International Conference on Robotics and Biomimetics*, pp. 1468–1473, December 2011.

[74] J. Liu and H. Peng, “Modeling and control of a power-split hybrid vehicle,” *IEEE Transactions on Control Systems Technology*, vol. 16, pp. 1242–1251, November 2008.

[75] G. Ripaccioli, D. Bernardini, S. D. Cairano, A. Bemporad, and I. V. Kolmanovsky, “A stochastic model predictive control approach for series hybrid electric vehicle power management,” in *American Control Conference*, (Baltimore, USA), pp. 5844–5849, June 2010.

[76] S. J. Moura, H. K. Fathy, D. S. Callaway, and J. L. Stein, "A stochastic optimal control approach for power management in plug-in hybrid electric vehicles," *IEEE Transactions on Control Systems Technology*, vol. 19, pp. 545–555, May 2011.

[77] J. S. Won and R. Langari, "Intelligent energy management agent for a parallel hybrid vehicle-Part II: Torque distribution, charge sustenance strategies, and performance results," *IEEE Transactions on Vehicular Technology*, vol. 54, pp. 935–953, May 2005.

[78] Q. Gong, Y. Li, and Z. Peng, "Power management of plug-in hybrid electric vehicles using neural network based trip modeling," in *American Control Conference*, pp. 4601–4606, June 2009.

[79] Y. Gao and M. Ehsani, "Parametric design of the traction motor and energy storage for series hybrid off-road and military vehicles," *IEEE Transactions on Power Electronics*, vol. 21, pp. 749–755, May 2006.

[80] M. Gokasan, S. Bogosyan, and D. J. Goering, "Sliding mode based powertrain control for efficiency improvement in series hybrid-electric vehicles," *IEEE Transactions on Power Electronics*, vol. 21, pp. 779–790, May 2006.

[81] L. Q. Jin, X. H. Zeng, and W. Wang, "The control strategy and cost analysis for series plug-in hybrid electric vehicle," in *Advanced Computer Control*, vol. 2, (Shanyang, China), pp. 350–354, June 2010.

[82] M. H. Hajimiri and F. R. Salmasi, "A predictive and battery protective control strategy for series HEV," *Journal of Asian Electric Vehicles*, vol. 6, pp. 1159–1165, December 2008.

[83] X. Liu, Y. Wu, and J. Duan, "Power split control strategy for a series hybrid electric vehicle using fuzzy logic," in *International Conference in Automation and Logistics*, (Qingdao, China), September 2008.

[84] X. Liu, Q. Fan, K. Zheng, J. Duan, and Y. Wang, "Constant SOC control of a series hybrid electric vehicle with long driving range," in *International Conference on Information and Automation*, (Harbin, China), pp. 1603–1608, June 2010.

[85] A. Poursamad and M. Montazeri, "Design of genetic fuzzy control strategy for parallel hybrid electric vehicles," *Control Engineering Practice*, vol. 16, pp. 861–873, July 2008.

[86] F. U. Syed, M. L. Kuang, J. Czubay, and H. Ying, "Derivation and experimental validation of a power-split hybrid electric vehicle model," *IEEE Transactions on Vehicular Technology*, vol. 55, pp. 1731–1747, November 2006.

[87] F. U. Syed, H. Ying, M. Kuang, S. Okubo, and M. Smith, "Rule-based fuzzy gain-scheduling PI controller to improve engine speed and power behavior in a power-split hybrid electric vehicle," in *Annual Meeting of the North American Fuzzy Information Processing Society*, pp. 284–289, June 2006.

[88] F. U. Syed, M. L. Kuang, M. Smith, S. Okubo, and H. Ying, "Fuzzy gain-scheduling proportional-integral control for improving engine power and speed behavior in a hybrid electric vehicle," *IEEE Transactions on Vehicular Technology*, vol. 58, pp. 69–84, January 2009.

[89] O. Sundstrom and L. Guzzella, "A generic dynamic programming matlab function," in *18th IEEE International Conference on Control Applications*, (Saint Petersburg, Russia), pp. 1625–1630, July 2009.

[90] E. D. Tate and S. P. Boyd, "Finding ultimate limits of performance for hybrid electric vehicles," *SAE Paper*, no. 00FTT-50, 1998.

[91] D. Karbowski, A. Rousseau, S. Pagerit, and P. Sharer, "Plug-in vehicle control strategy: From global optimisation to real-time application," *International Electric Vehicle Symposium*, vol. 22, pp. 1–12, October 2006.

[92] A. Konev and L. Lezhnev, "Control strategy optimization for a series hybrid vehicle," *SAE Technical Paper Series*, April 2006.

[93] S. Delprat, J. Lauber, T. M. Guerra, and J. Rimaux, "Control of a parallel hybrid powertrain: Optimal control," *IEEE Transactions on Vehicular Technology*, vol. 53, pp. 872–881, May 2004.

[94] J. F. Bonnans, T. Guilbaud, A. K. Cherif, D. von Wissel, C. Sagastizábal, and H. Zidani, "Parametric optimization of hybrid car engines," *Optimisation and Engineering, Springer*, vol. 5, pp. 395–415, December 2004.

[95] L. V. Perez, G. R. Bossio, D. Moitre, and G. O. Garcia, "Optimization of power management in an hybrid electric vehicle using dynamic programming," *Mathematics and Computers in Simulation*, vol. 73, pp. 244–254, July 2006.

[96] Q. Gong, Y. Li, and Z. R. Peng, "Trip based power management of plug-in hybrid electric vehicle with two-scale dynamic programming," in *IEEE Vehicle Power and Propulsion Conference*, pp. 12–19, September 2007.

[97] P. Pisu, K. Koprubasi, and G. Rizzoni, "Energy management and drivability control problems for hybrid electric vehicles," in *IEEE Conference on Decision and Control, and the European Control Conference*, 44, (Seville, Spain), pp. 1824–1830, December 2005.

[98] J. Chiasson and L. Tolbert, "A library of simulink blocks for real-time control of HEV traction drives," *SAE Paper*, no. 02FCC-30, 2002.

[99] "www.asso-ppnmc.fr, Noao, vehicule electrique avec prolongateur d'autonomie. Pole de la Performance Nevers Magny-Cours. Accessed 12 february 2014.."

[100] "www.circuitmagnycours.com., Pistes et pilotage, La piste Grand Prix. Accessed 12 february 2014.."

[101] F. Rodriguez, "PPNMC range extender control documentation," tech. rep., TMG, Magny Cours, Nevers, France, December 2011.

[102] L. Guzella and A. Amstutz, "The QSS toolbox manual," tech. rep., IMRT Measurement and Control Laboratory, June 2005.

[103] Z. Asus, D. Chrenko, E. H. Aglzim, A. Keromnes, and L. Le-Moyne, "Simple method of estimating consumption of internal combustion engine for hybrid application," in *IEEE Transportation Electrification Conference and Expo (iTEC)*, (Michigan, USA), June 2012.

[104] L. Horrein, A. Bouscayrol, and M. El-Fassi, "Thermal energetic model of an internal combustion engine for simulation of a thermal vehicle," in *IEEE Vehicle Power and Propulsion Conference*, (Seoul, Korea), Octobre 2012.

[105] J. B. Heywood, *Internal Combustion Engine Fundamentals*. USA: McGraw-Hill Inc., 1988.

[106] P. Guibert, "Modélisation du cycle moteur: Approche zérodimensionnelle," *Techniques de l'Ingénieur*, no. BM 2 510, p. 16, 2010.

[107] A. Bouscayrol, B. Davat, B. de Fornel, B. Francois, J. Hautier, F. Meibody-Tabar, E. Monmasson, M. Pietrzak-David, H. Razik, E. Semail, and F. Benkhoris, "Control structures for multi-machine multi-converter systems with upstream coupling," *Mathematics and Computers in Simulation*, vol. 63, pp. 261–270, November 2003.

[108] D. Chrenko, J. Coulié, M.-C. Péra, and D. Hissel, "Static and dynamic modeling of a diesel fuel processing unit for polymer electrolyte fuel cell supply," *International Journal of Hydrogen Energy*, vol. 34, pp. 1324–1335, 2009.

[109] A. Bouscayrol, W. Lhomme, P. Delarue, B. Lemaire-Semail, and S. Aksas, "Hardware-in-the-loop simulation of electric vehicle traction systems using energetic macroscopic representation," in *32nd Annual Conference on IEEE Industrial Electronics*, (Paris, France), November 2006.

[110] W. Lhomme, A. Bouscayrol, and P. Barrade, "Simulation of a series hybrid electric vehicle based on energetic macroscopic representation," in *IEEE International Symposium on Industrial Electronics*, 2004.

[111] A. L. Allégre, A. Bouscayrol, and R. Trigui, "Flexible real-time control of a hybrid energy storage system for electric vehicles," *IET Electrical Systems in Transportation*, vol. 3, pp. 79–85, March 2013.

[112] J. S. Martínez, D. Hissel, M.-C. Péra, and M. Amiet, "Practical control structure and energy management of a testbed hybrid electric vehicle," *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 4139–4152, November 2011.

[113] W. Lhomme, R. Trigui, P. Delarue, B. Jeanneret, A. Bouscayrol, and F. Badin, "Switched causal modeling of transmission with clutch in hybrid electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 57, pp. 2081–2088, July 2008.

[114] L. Roberto and E. Simos A., “Lap time optimisation of a sports series hybrid electric vehicle,” in *Proceedings of the World Congress on Engineering*, vol. III, July 2013.

[115] A. E. Fitzgerald, C. J. Kingsley, and S. D. Umans, *Electric Machinery.* Mc Graw Hill, 2003.

[116] S. A. Evangelou and A. Shukla, “Advances in the modelling an control of series hybrid electric vehicles,” in *American Control Conference*, (Montreal, Canada), pp. 527–534, June 2012.

[117] P. Delarue, A. Bouscayrol, and E. Semail, “Generic control method of multileg voltage-source-converters for fast practical implementation,” *IEEE Transactions on Power Electronics*, vol. 18, pp. 517–526, March 2003.

[118] Z. H. Che Daud, D. Chrenko, F. Dos Santos, E.-H. Aglzim, and L. Le Moyne, “Electro-thermal simulation of lithium ion batteries for electric and hybrid vehicles,” in *Simulation for Energy, Sustainable Development and Environment (SESDE)*, (Athens, Greece), September 2013.

[119] N. Watrin, D. Bouquain, B. Blunier, and A. Miraoui, “Multiphysic lithium-based battery pack modelling for simulation purposes,” in *IEEE Vehicle Power and Propulsion Conference (VPPC)*, (Chicago, IL. USA), September 6-9 2011.

[120] S. J. Andreasen, L. Ashworth, I. N. M. Remón, and S. K. Koer, “Directly connected series coupled htpem fuel cell stacks to a li-ion battery dc bus for a fuel cell electrical vehicle,” *International Journal of Hydrogen Energy*, vol. 33, pp. 7137–7145, November 2008.

[121] M. Ceraolo, C. Miulli, and A. Pozio, “Modelling static and dynamic behaviour of proton exchange membrane fuel cells on the basis of electro-chemical description,” *Journal of Power Sources*, vol. 113, pp. 131–144, September 2002.

[122] Y. Wu and H. Gao, “Optimization of fuel cell and supercapacitor for fuel-cell electric vehicles,” *Vehicular Technology, IEEE Transactions on*, vol. 55, no. 6, pp. 1748–1755, 2006.

[123] “www-liten.cea.fr, Technologies GENEPAC de PSA Peugeot Citroen. Accessed 11 february 2013..”

[124] C. He, S. Desai, G. Brown, and S. Bollepalli, “PEM fuel cell catalysts: Cost, performance, and durability,” in *The Electrochemical Society*, Interface, 2005.

[125] M. J. Kim, H. Peng, C.-C. Lin, E. Stamos, and D. Tran, “Testing, modeling, and control of a fuel cell hybrid vehicle,” in *American Control Conference*, (Portland, USA), June 2005.

[126] D. Feroldi, M. Serra, and J. Riera, “Energy management strategies based on efficiency map for fuel cell hybrid vehicles,” *Journal of Power Sources*, vol. 190, pp. 387–401, February 2009.

[127] A. Ravey, N. Watrin, B. Blunier, D. Bouquain, and A. Miraoui, "Energy-source-sizing methodology for hybrid fuel cell vehicles based on statistical description of driving cycles," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 9, pp. 4164–4174, 2011.

[128] E. Tazelaar, B. Veenhuizen, P. van den Bosch, and M. Grimminck, "Analytical solution of the energy management for fuel cell hybrid propulsion systems," *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 5, pp. 1986–1998, 2012.

[129] A. Vahidi, A. Stefanopoulou, and H. Peng, "Current management in a hybrid fuel cell power system: A model-predictive control approach," *IEEE Transactions on Control Systems Technology*, vol. 14, pp. 1047–1057, November 2006.

[130] S. Kelouwani, N. Henao, K. Agbossou, Y. Dube, and L. Boulon, "Two-layer energy-management architecture for a fuel cell hev using road trip information," *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 9, pp. 3851–3864, 2012.

[131] C. H. Zheng, C. E. Oh, Y. I. Park, and S. W. Cha, "Fuel economy evaluation of fuel cell hybrid vehicles based on equivalent fuel consumption," *International Journal of Hydrogen Energy*, vol. 37, pp. 1790–1796, November 2011.

[132] A. Ravey, B. Blunier, S. Lukic, and A. Miraoui, "Control strategy of fuel cell hybrid electric vehicle based on driving cycle recognition," in *IEEE Transportation Electrification Conference and Expo (iTEC)*, (Michigan, USA), June 2012.

[133] J. P. Torreglosa, P. García, L. M. Fernández, and F. Jurado, "Predictive control for the energy management of a fuel cell-battery-supercapacitor tramway," *IEEE Transactions on Industrial Electronics, Unpublished*, 2013.

[134] M. Sorrentino, C. Pianese, and M. Maiorino, "An integrated mathematical tool aimed at developing highly performing and cost-effective fuel cell hybrid vehicles," *Journal of Power Sources*, vol. 221, pp. 308–317, August 2012.

[135] B. Blunier and A. Miraoui, *Piles a combustible*. Paris: Ellipses, 2007.

[136] D. Feroldi and M. Basualdo, *PEM Fuel Cells with Bio-Ethanol Processor Systems*, ch. Description of PEM Fuel Cells System, pp. 49–72. Springer-Verlag, 2012.

[137] A. Tani, M. B. Camara, B. Dakyo, and Y. Azzouz, "DC/DC and DC/AC converters control for hybrid electric vehicles energy management-ultracapacitors and fuel cell," *IEEE Transactions on Industrial Electronics*, vol. 9, pp. 686–696, May 2013.

[138] L. Guzzella and C. H. Onder, *Introduction to Modeling and Control of Internal Combustion Engine Systems*. Zurich, Switzerland: Springer, 2nd ed., 2009.

[139] O. Sundstrom, L. Guzzella, and P. Soltic, "Optimal hybridization in two parallel hybrid electric vehicles using dynamic programming," in *The International Federation of Automatic Control*, July 2008.

[140] Z. Asus, E. H. Aglzim, D. Chrenko, and L. Le-Moyne, “Parametric design and sizing of a fuel cell hybrid electric racing car,” in *Fundamentals and Development of Fuel Cells (FDFC)*, (Karlsruhe, Germany), April 2013.

[141] R. Bellman, “The theory of dynamic programming,” *The RAND Corporation*, 1954.

[142] D. Chrenko, I. Garcia Diez, and L. Le Moyne, “Artificial driving cycles for the evaluation of energetic needs of electric vehicles,” in *IEEE Transportation Electrification Conference and Expo (iTEC)*, June 2012.

[143] E. Tzirakis, K. Pitsas, F. Zannikos, and S. Stournas, “Vehicle emissions and driving cycles: Comparison of the Athens driving cycle (ADC) with ECE-15 and European driving cycle (EDC),” *Global NEST*, vol. 8, pp. 282–290, May 2006.

[144] M. Andre, “The ARTEMIS european driving cycles for measuring car pollutant emissions,” *Science of the Total Environment*, vol. 334-335, pp. 73 – 84, April 2004.

[145] N. Kim, A. Rousseau, and M. Duoba, “GM Volt vehicle model development and validation under different thermal conditions,” *Ingenieurs de l’Automobile*, no. 827, pp. 35–40, 2013.

Abstract:

The main objectives of this work is to develop an effective modeling method for an easy deployment of a control strategy, to review and study an optimal control strategy for a specific application, and to analyze improvement that can be effected to engine for better efficiency in hybrid vehicle architecture. The scopes of this work include the simulation part of the studied system and its validation with experimental results. Study cases are used to analyze optimization that can be effected to the original system. A well established optimization tool is chosen to optimize the actual control strategy and becomes a benchmark of a new optimal control strategy to be deployed in the system. A predictive method to know energy consumption of the system is developed in order to obtain an optimal control suitable with the vehicle application. Using the developed model, analysis is conducted to identify an optimal control strategy for a specific utilization. As perspectives, the main components of the system can be studied for improvements of its energy efficiency. The Energetic Macroscopic Representation (EMR) is a good method to represent dynamic model and it can be used to model any electromechanical machines and can be envisaged to model other system than a vehicle system, like a renewable energy system, a new electro-mechanical system or a robotic system.

Keywords: hybrid electric vehicle, effective modeling, optimal control strategy, and energy efficiency.

Résumé:

Les principaux objectifs de ce travail est de développer une méthode de modélisation efficace pour un déploiement facile et rapide d'une stratégie de contrôle, d'examiner et d'étudier cette stratégie pour une application spécifique, et d'analyser l'amélioration qui peut être apporté à un moteur pour une meilleure efficacité dans les systèmes électrique et hybride. Ce travail comprend une partie simulation du système étudié et sa validation avec les résultats expérimentaux. Les études de cas sont utilisées pour analyser l'optimisation qui peut être effectuée en comparaison au système d'origine (le véhicule étudié est la NOAO). Un outil d'optimisation est choisie pour optimiser la stratégie de contrôle actuellement déployée sur le véhicule. Cette outil nous a permis de développer une nouvelle stratégie de commande optimisée prêt à être déployé dans le véhicule. Un procédé de prédiction pour connaître la consommation d'énergie du système est mis au point en vue d'obtenir un contrôle optimal adapté à la demande du véhicule et à une utilisation spécifique.

Comme perspectives, les principaux composants du système peuvent être étudiés et modélisé afin d'améliorer l’efficacité énergétique du véhicule. La Représentation Energétique Macroscopique (REM) est une bonne méthode pour représenter le modèle dynamique et peut être utilisé pour modéliser des machines électromécaniques. Cette méthode est également envisagé pour modéliser d’autre système que le système véhicule tel que les systèmes énergies renouvelables, les systèmes électromécanique ou robotique.

Mot clés: véhicule électrique hybride, modélisation efficace, la stratégie de contrôle optimale, et l’efficacité énergétique.

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