

Research Article

Adaptive ECMS for Hybrid Electric Vehicles Based on SOC Feedback

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Abstract

The negative impact of atmospheric pollutants emitted by mobile vehicles on human health and environment have been increasingly attracting the attention of public and private policy makers. Those entities and many other have been working together to ensure that emissions related to the consumption of fossil fuels are considerably minimize. One of the main authors of this problem seems to be the means of displacement we are using every day, thermal cars. It is therefore necessary to explore and develop more economical approaches and modern alternatives for vehicle energy consumption. It is within this framework that automobile manufacturers, in collaboration with researchers, are committed to developing new forms of transport, the most ideal of which are electric vehicles and hybrid electric vehicles. This paper discusses the modeling and optimization of energy management of hybrid electric vehicles. The article develops an energy management system to minimize the energy consumption of a hybrid electric vehicle. Hybrid electric vehicle control is managed by the Adaptive Equivalent Consumption Minimization Strategy (A_ECMS). This strategy performs an update of the equivalence factor through the battery state of charge feedback method. The simulation results shown that the A_ECMS approach achieved an average fuel saving of nearly 40% for FTP-75 driving cycle and 13% for the class cycle.

Keywords

Plug-in Hybrid Vehicle, Energy Management Strategy, A_ECMS, Equivalent Factor, K-means

1. Introduction

Although they have been playing major roles in the human's life over the last centuries, mobile vehicles are considered today one of the main sources contributing in numerous issues that has been facing our planet. Some of these adverse effects include the increase of atmospheric pollution, recurrent cardiovascular problems, emission of greenhouse

gases contributing to global warming, and the weariness of fossil fuels [1].

Regarding those increasing problems, there is an urgent need to accommodate the modern transportation means in order to cope with the anti-pollution standards implemented by the governments to limit harmful emissions. It is with this

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in mind that the automobile industry to develop more economical technologies in terms of fuel consumption in order to reduce the emission of CO₂, polluting gases and the depletion of oil. The most ideal solution is the electrification of the vehicle powertrain. The electric vehicle is powered by an electric motor powered by a battery. It is a vehicle with no CO₂ emissions since it does not require any combustion of fossil fuels. In addition, its traction chain has the advantage of allowing the reproduction of electrical energy through regenerative braking. However, due to the use of the battery, the electric vehicle does not constitute a viable alternative to the thermal vehicle because it has two major disadvantages: the low autonomy compared to the thermal vehicle and the cost [2-4].

In a hybrid vehicle, the torque to the wheels is provided by one or both energy chains. The objective of energy management is to find the distribution of power flows between the two traction chains, which minimizes fuel consumption while ensuring a given final state of charge of the battery. The algorithms for solving this problem called "energy management strategies or methods"

are classified into three categories namely rule-based methods, optimization methods and artificial intelligence methods. Rule-based methods are strategies based on empirical rules derived from the experiences acquired by experts on the behavior of the various components of the powertrain. These strategies include the thermostat method, the power tracking method, the state machine, and fuzzy logic [5].

Optimization methods are methods for modeling a system and formulating the optimization problem in order to find solutions. Optimization methods are classified according to whether they can be implemented in real time (online strategies) or are intended solely for simulation (global optimization methods). Offline global optimization methods are based on a priori knowledge of the speed profile. These methods include dynamic programming (DP), Genetic Algorithms (GA), simulated annealing, and Particle Swarms Optimization (PSO).

Online optimization methods are strategies that can be implemented on real vehicle computers. These methods include the Equivalent Consumption Minimization Strategy (ECMS), the Pontryagin Maximum Principle (PMP), and model predictive control [3, 5].

Artificial intelligence methods are strategies that allow the energy management system to learn to adapt to driving conditions in order to optimize energy distribution in real time. These are deep learning method, supervised learning method and reinforcement learning method [3, 5].

The choice of the ECMS algorithm is motivated by its merits in terms of proven optimization potential and the possibility of its real-time implementation. The ECMS algorithm exists in its classic version with an invariable equivalence factor and its adaptive variant. Given the real driving conditions which are constantly changing, we chose to carry out this work with the adaptive ECMS. This will allow the

equivalence factor to be updated according to the variation of driving conditions and styles. Three other algorithms are registered to carry out the adaptation of the equivalence factor, namely the PI controller, artificial neural networks and dynamic programming. This first article is devoted to the results obtained with the PI controller. The adaptation with artificial neural networks and dynamic programming is in progress. The PI controller minimizes the error between the target SOC and the current SOC.

2. Architectures of Hybrid Electric Vehicle

Several types of hybrid vehicle architectures have been investigated from the literature [1, 6]. Among them, the serial and parallel architectures have drawn attention from many authors [1, 6].

2.1. Serial Architecture

In a serial architecture as illustrated in Figure 1, the power passes from the thermal engine to the electric motor which is responsible exclusively for traction of the vehicle. The connection between the two motors is an electrical connection via a generator which transforms mechanical energy into electrical energy that is later injected into the electrical chain [1, 6].

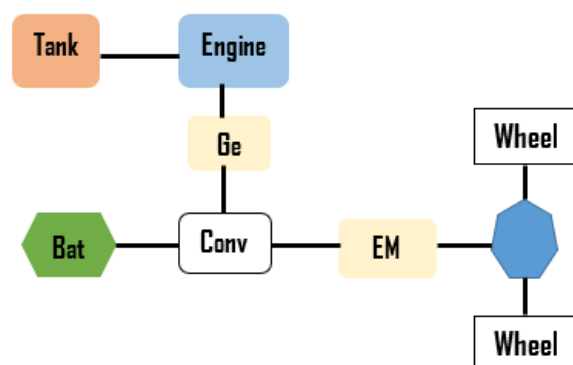


Figure 1. Serial hybrid architecture.

2.2. Parallel Architecture

In a parallel architecture, the two motors are directly coupled to the wheels. The power supplied to the wheels is the combination of the powers supplied by the two engines. This means the two engines can therefore participate simultaneously or independently in the propulsion of the vehicle. This is currently one of the most used architectures, since it exhibits numerous advantages over serial architecture. A wide range of car manufacturers employs this architecture to develop their products [1, 6].

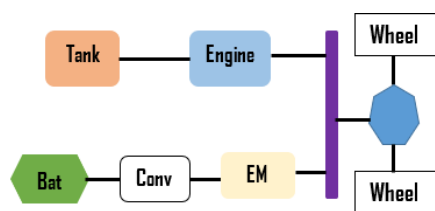


Figure 2. Parallel hybrid architecture.

Where, EM, Bat, Conv, and Ge stand for Electrical Motor, Battery, Converter, and Generator, respectively.

There are many other architectures including serial-parallel and complex architectures. These architectures are more complex, more expensive but combine the advantages of both serial and parallel architectures. Table 1 lists the advantages and disadvantages of all the aforementioned architectures.

Table 1. Advantages and disadvantages of various architectures of hybrid vehicle [1, 6].

Architecture	Benefits	Disadvantages
Serial	Less polluting Ease of control	Low global efficiency large size of EM High-cost
Parallel	All-electric mode Good overall efficiency Energy recovery during regenerative braking	Torque break when loading gearbox ratios
Serial/Parallel	Combine the advantages of HS and HP	Complexity in the control High-cost

2.3. Parallel Hybrid Architecture Chosen

The proposed hybrid vehicle architecture is illustrated in Figure 3.

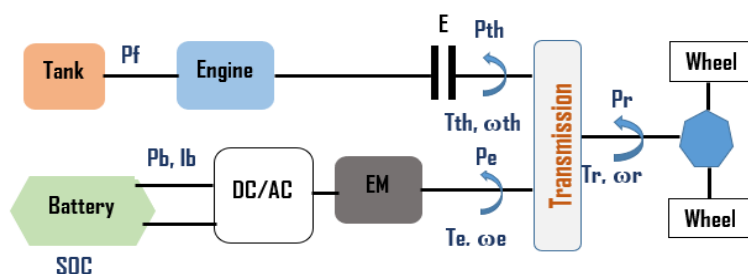


Figure 3. Proposed parallel hybrid architecture.

This architecture consists of two energy conversion chains. The thermal chain consists of a tank that stores the fuel, the internal combustion engine that converts the fuel into thermal energy, and the clutch that connects and disconnects the internal combustion engine to the transmission. The electrical or thermal energy is converted into mechanical energy by the crankshaft system. This mechanical energy is transmitted to the drive wheels in the form of kinetic energy to propel the vehicle.

The electrical chain consists of battery, inverter, and electric motor. The battery is the source of electrical energy. It provides voltage to the converter (inverter). The latter transforms this voltage into a three-phase voltage system that can be used by the electric motor. The displacement of the vehicle

is characterized by the required factors, including the power, the torque, and the speed. The required power can be exclusively provided either by the engine or by the electric motor, or by both.

3. Equivalent Consumption Minimization Strategy (ECMS)

3.1. Presentation

Considered as one of the main orientations in the area of research related to energy management strategies, ECMS is a local optimization algorithm first developed in 1999 by Pa-

ganelli [7]. In ECMS strategies, the main purpose of an optimization problem is to determine a key parameter referred to as equivalence factor; allowing the state of charge of the battery to be maintained around a target reference value. This Equivalence factor is a conversion factor between electrical energy and thermal energy. It enables to bring energy consumption into the same energy space in order to determine the optimal control variables [7-26].

Several variants of the ECMS exist depending on how the equivalence factor is evaluated and whether or not the available external information is integrated. This information includes traffic information, driver information, or vehicle information. In the non-adaptive variants (Non-Adaptive ECMS) the values of the equivalence factor are initially chosen while the adaptive variants (Adaptive ECMS) enable the equivalence factor to be updated at each moment of the journey. The values of equivalence factor are selected based on prediction levels of future driving conditions. ECMS by telemetry (Telemetry ECMS) uses information provided by the navigation system to update the equivalence factor [6, 7].

In offline ECMS methods, the equivalent factor is optimized using some optimization algorithms such as particle swarm optimization (PSO), and genetic (GA) algorithms.

This method involves the evaluation of the cost function as a sum of fuel consumption and corrected fuel consumption. The corrected consumption is calculated using the variation in the battery state of charge.

As the consumption of the fuel source and the electrical

source are not directly comparable, an equivalence factor is necessary. This factor can be calculated by the average energy trajectories of the vehicle sources. As the efficiency of the different component may vary between areas of operation, this methodology is valid for evaluating the average values [7-26].

In ECMS approaches, the battery is considered an auxiliary fuel tank. This enables the choice of the control variables at any moment; yielding to the minimization of the total energy taken from the two tanks via an equivalence factor. Moreover, this eases the possibility to convert the electrical energy into mechanical energy; bringing back the two consumptions in the same energy space.

The energy distribution by the two sources obeys two cases:

The first case is a discharge of the battery at instant t . This corresponds to a quantity of electrical energy taken from the battery at that moment. This quantity of energy must be restored to the battery during the instant $t' > t$. At this time, the quantity of fuel consumed must guarantee the traction of the vehicle and participate in recharging the battery [11].

The second case corresponds to the storage of electrical energy in the battery (recharging the battery) at a time t . At the instant $t' > t$, the stored energy will contribute to both the traction of the vehicle and fuel economy [11].

The energy distribution of the hybrid vehicle according to the operating mode is illustrated in Figure 4.

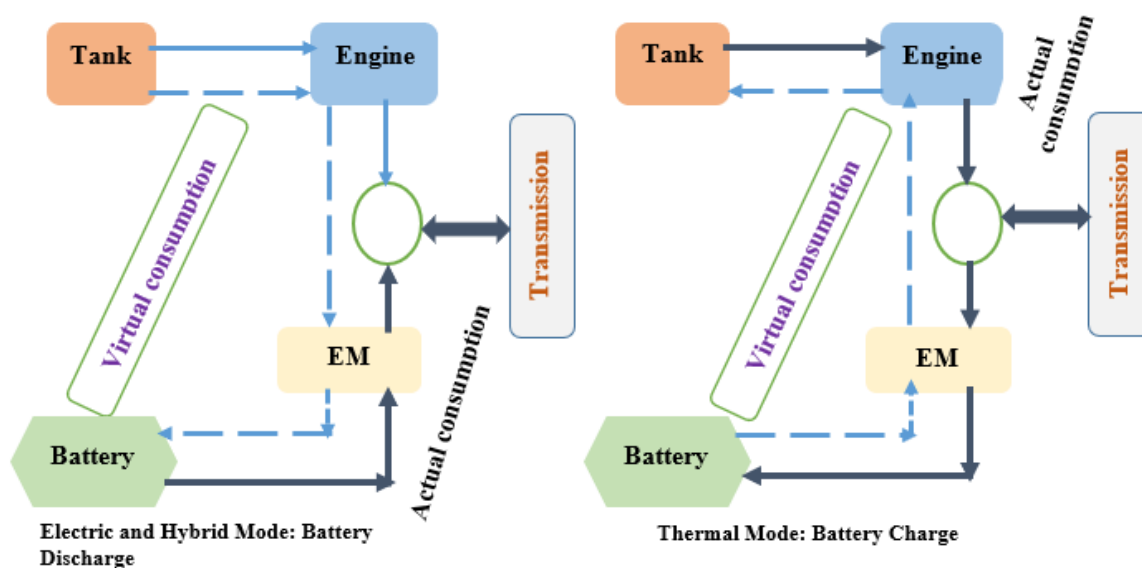


Figure 4. Energy distribution of the hybrid vehicle.

This figure shows how the ECMS algorithm works in converting electrical and thermal energy to bring both consumptions into the same energy range across the three operating modes.

In electric and hybrid mode, the electric motor contributes

to the vehicle's traction by consuming electrical energy. This actual electrical energy consumption is converted into its fuel equivalent (virtual consumption), which will be released in thermal mode.

In thermal mode, the engine provides traction by consum-

ing fuel. This actual fuel consumption is converted into its electrical equivalent (virtual consumption), which will be released later in electric mode.

The original expression of the ECMS algorithm proposed by Paganelli is expressed from equations (12) to (17) [10, 11].

$$\dot{m}_{eq}(t) = \dot{m}_c(t) + \dot{m}_b(t) \quad (1)$$

Where $\dot{m}_{eq}$, $\dot{m}_c$, $\dot{m}_b$ are the total equivalent instantaneous consumption, the instantaneous fuel consumption and the instantaneous electrical energy consumption, respectively.

Instantaneous consumption of fuel and electrical energy is expressed according to the characteristics of engine and electric motor.

$$\dot{m}_c(t) = \frac{P_{th}(t)}{\eta_{th}(t)Q_{LHV}} = \frac{P_r(t)u(t)}{\eta_{th}(t)Q_{LHV}} \quad (2)$$

$$\dot{m}_b(t) = \frac{s}{Q_{LHV}} P_b(t) = \frac{s}{Q_{LHV}} P_r(t)(1-u(t)) \quad (3)$$

$$\dot{m}_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t)Q_{LHV}} + \frac{s(t)P_b(t)}{Q_{LHV}} \quad (4)$$

$$\dot{m}_{eq}(t) = \frac{1}{\eta_{th}(t)Q_{LHV}} P_r(t)u(t) + \frac{s}{Q_{LHV}} P_r(t)(1-u(t)) \quad (5)$$

Where P_{th} is the power of the engine, P_r the required power, u the control variable vector, P_b the power of the battery, Q_{LHV} the minimum released heat due to fuel combustion, η_{th} the efficiency of the engine, and s the equivalence factor.

To ensure battery safety, we define a penalty factor based on the SOC instantly and allowing to maintain it between its limit values. This penalty factor is attributed to the consumption of electrical energy. It allows the use of electrical energy when the SOC is close to the maximum SOC of the battery and to switch to the thermal engine when the SOC is close to the minimum SOC. This facilitates the delimitation of the SOC between the two values and its maintenance around a target SOC. This SOC target should be specified based on battery efficiency [25].

$$p(SOC) = 1 - \left(\frac{SOC(t) - SOC_{cible}}{0.5(SOC_{max} - SOC_{min})} \right)^a \quad (6)$$

Where $p(SOC)$ is the penalty and a the penalty factor

$$\dot{m}_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t)Q_{LHV}} + \frac{s(t)P_b(t)}{Q_{LHV}} * p(SOC) \quad (7)$$

The equivalent power is expressed by:

$$P_{eq} = \dot{m}_{eq} * Q_{LHV} \quad (8)$$

$\dot{m}_{eq}$ is the equivalent mass

$$P_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t)} + s(t)P_b(t) * p(SOC) \quad (9)$$

The power of the engine is expressed as a function of the crankshaft torque and the engine speed.

$$P_{th} = T_{th}\omega_{th} \quad (10)$$

T_{th} is the crankshaft torque

ω_{th} is the speed of engine

$$\eta_{th} = \frac{P_{th}}{P_c} \quad (11)$$

P_c is the thermodynamic power associated with the fuel

$$P_c = m_f H_{PCI} \quad (12)$$

m_f is the mass of fuel

H_{PCI} is the lower calorific value of the fuel

$$P_{th}(t) = u^*(t)P_r(t) \quad (13)$$

$$P_b(t) = (1 - u^*(t))P_r(t) \quad (14)$$

$u^*(t)$ is the optimal solution of the control variables.

3.2. Adaptive ECMS Strategies for Hybrid Electric Vehicles Based on SOC Feedback

The equivalence factor update is performed with a PI controller. The latter minimizes the error between the target SOC and the instantaneous SOC.

$$s(t) = s_0 + k_p((\varepsilon(t)).\varepsilon(t) + k_i \int_{t_0}^{t_f} \varepsilon(\tau) d\tau \quad (15)$$

Where S_0 is the initial equivalence factor, K_p the proportional corrector gain, K_i the integral corrector gain.

The role of proportional correction is to ensure battery charging when the SOC approaches its lower limit value, and symmetrically to ensure battery discharge when the SOC approaches its upper limit value.

The role of integral correction is to center the SOC trajectory around target SOC in the case where the optimal equivalence factor estimation error results in the appearance of a static error.

$$\varepsilon(t) = SOC_{target}(t) - SOC(t) \quad (16)$$

Where ε is the error between the target SOC and the current

SOC.

Figure 5 shows the diagram of the A_ECMS algorithm.

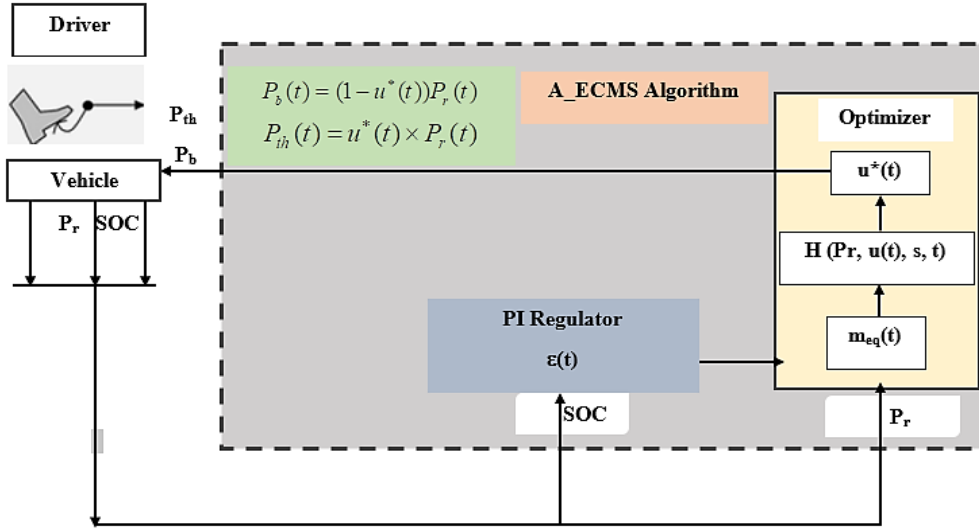


Figure 5. Diagram of A_ECMS.

When the driver presses the accelerator pedal, they express a power requirement that is sent to the control system based on the A_ECMS algorithm. The control system evaluates the energy level available in the battery through its state of charge

and distributes the required power between the energy chains. The power that each of the two motors will have to provide is then sent to them.

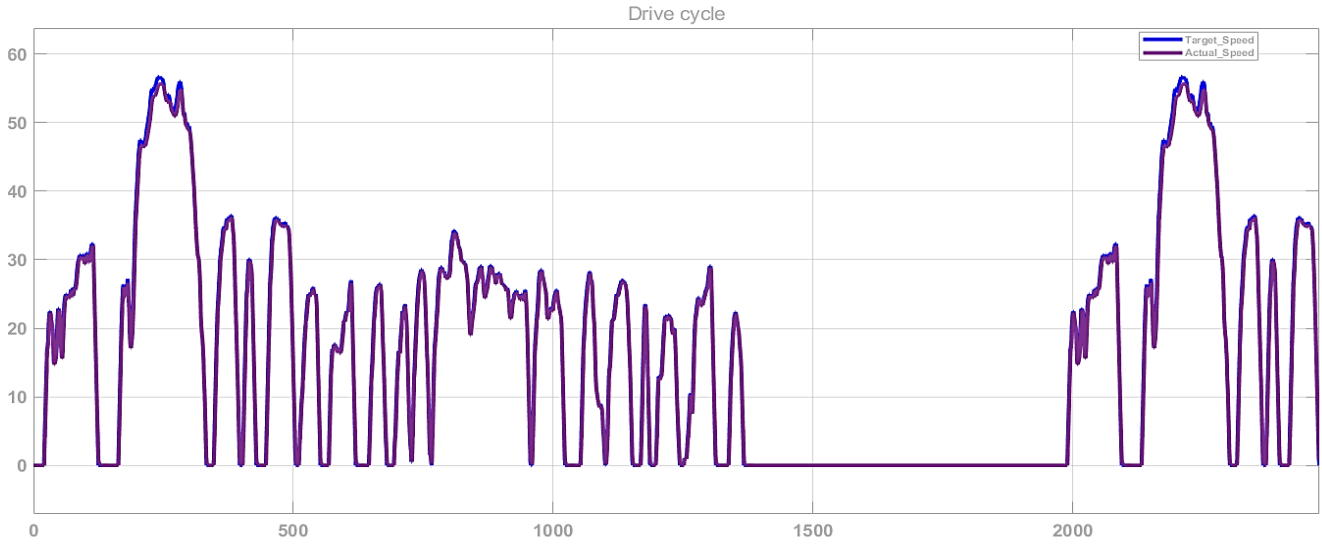


Figure 6. Reference speed and vehicle speed.

3.3. Emission of Atmospheric Pollutants

The masses of air pollutants emitted by the vehicle are estimated by equations 18, 19, 20 and 21 from the Panis [26] and Tobias [27] models.

$$m_{CO_2} = 1000 \int_0^t \dot{m}_{CO_2} v(t) dt \quad (17)$$

$$m_{CO} = 1000 \int_0^t \dot{m}_{CO} v(t) dt \quad (18)$$

$$m_{HC} = 1000 \int_0^t \dot{m}_{HC} v(t) dt \quad (19)$$

$$m_{NOx} = 1000 \int_0^t \dot{m}_{NOx} v(t) dt \quad (20)$$

Where m_{CO_2} , m_{CO} , m_{HC} , m_{NOx} are mass emitted of CO_2 , CO , CO and NOx , respectively.

And $\dot{m}_{CO_2}$, $\dot{m}_{CO}$, $\dot{m}_{HC}$, $\dot{m}_{NOx}$ are mass flow rate of CO_2 , CO , CO and NOx , respectively, v is the speed of vehicle.

3.4. Drives Cycles

A driving cycle is the representation of vehicle speed versus time during a given trip. The speed cycle includes road conditions and driving style. Standardized speed cycles are speed cycles set up to represent certain particular road conditions to carry out simulations and experimental tests.

Firstly, the FTP-75 (Federal Test Protocol) speed cycle is used first and then a set of classified speed cycles.

The FTP-75 driving cycle simulates a 17.9 km urban route in 31 minutes.

Figure 6 shows the FTP-75 speed cycle. This cycle is made up of three phases: First phase of 505s with a cold start,

second phase of 864s and a third phase of 500s with a hot start after a 10-minute stop.

The vehicle speed has almost the same shape as the reference speed of the driving cycle. To observe overall compliance with the speed instructions.

Secondly, forty-five (45) speed cycles were downloaded into the ADVISOR. ADVISOR is a software simulation program based on MATLAB/Simulink. This program aims to evaluate the energy consumption of conventional, hybrid and electric vehicles in order to analyze energy management performance and fuel economy. The forty-five (45) driving cycles are categorized into three classes using the K-means algorithm. K-means is an automatic classification algorithm making it possible to identify groups of speed cycles which have similar characteristics, that is to say which are distinguished from each other in a significant way. Thus, for a given integer K, the algorithm categorizes the set of speed cycles into K clusters (K classes), where K is equal to three (3).

The Figure 7 shows the three classes of speed cycles after clustering.

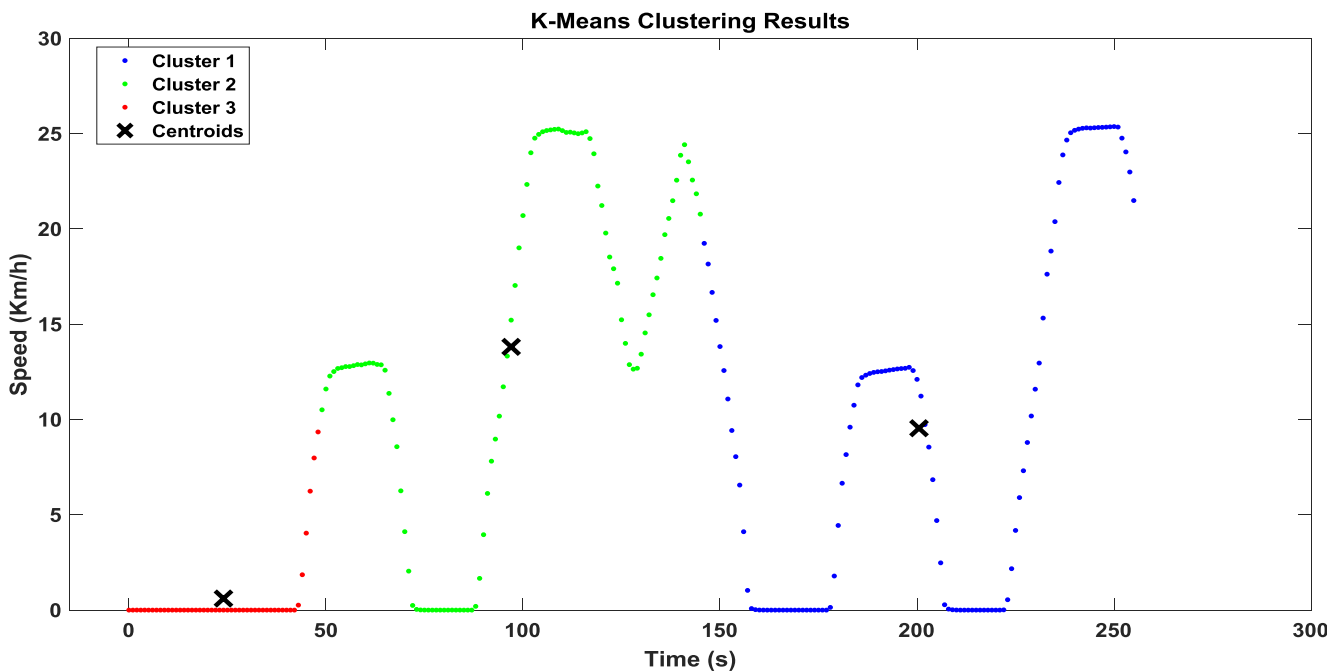


Figure 7. Driving cycle classes.

Speed cycles are classified according to speed ranges, which often depend on driving conditions and styles.

Class 1 = Phase 1: Driving cycle classes for urban and semi-urban roads (low speeds).

Class 2 = Phase 2: Driving cycle classes for highways (medium and high speeds).

Class 3 = Phase 3: Driving cycle classes for urban and semi-urban roads (medium and high speeds).

The k-means algorithm is based on evaluating the distance between observations and the centroids of the clusters. This

distance can be determined using functions for measuring the dissimilarity between observations such as Euclidean distance, Manhattan distance and Minkowski distance [28].

When the algorithm is executed, K observations are arbitrarily chosen as initial centroids of the K clusters.

For a number n of observations in an n-dimensional space, the Euclidean distance between each centroid c_i and each observation u_i is:

$$d(u_i, c_i) = \sqrt{(x_{ui} - x_{ci})^2 + (y_{ui} - y_{ci})^2} \quad (21)$$

Each observation is associated with the cluster whose centroid is the closest among the k centroids initially chosen randomly, that is to say whose centroid distance is minimal.

$$[\alpha, clusterX] = \min(d(u_i, c_i)) \quad (22)$$

Then, each of the observations is associated with the cluster whose center is closest to this observation in relation to all the centers of the other clusters.

The cluster centroids are again chosen from the observations of these clusters and the Euclidean distances between each centroid and each observation are recalculated using the current cluster memberships. Likewise, the association of the different observations with the closest new clusters is carried

out again. This process is repeated until the convergence criterion is reached. The convergence criterion is reached when there is no real change between two successive operations [29, 30].

4. Simulations

The simulations are carried out in matlab/simulink using the model of a parallel hybrid vehicle provided by Math-Works.

The simulations carried out highlight the energy flows and their distribution according to the different operating modes of the hybrid vehicle.

Figure 8 shows the diagram of simulation in Simulink environment.

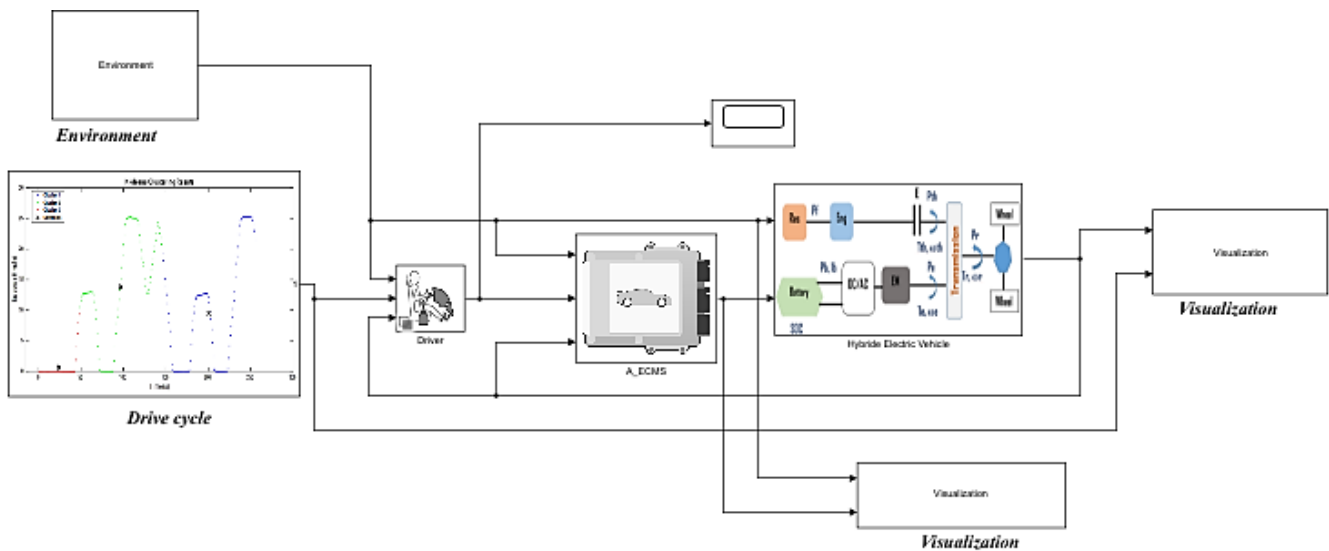


Figure 8. Diagram of simulation in Simulink.

The parameters of the Vehicle components are given in Table 2.

Table 2. Vehicle components.

Component	Type
Engine	Spark ignition Engine
Electric motor	Permanent magnet synchronous motor
Battery	Lithium Ion Battery

The driver model simulates a human driver through a predictive controller that minimizes the error between a set speed and the actual speed of the vehicle.

The parameters of the A_ECMS algorithm are given in Table 3.

Table 3. Parameters of the A_ECMS algorithm.

Size	Value
Equivalence factor	4.76
Harm factor	3
Proportional gain, ECMS_Kp	4
Integral gain, ECMS_Ki	2
Target state of charge	60
Maximum state of charge	80
Minimum state of charge	40

5. Results and Analysis

5.1. Simulation Results with FTP-75 Driving Cycle

The controller receives instructions from the accelerator pedal deduced from the FTP-75 (Federal Test Protocol) driving cycle and generates torque commands from the

thermal and electric motors.

Figure 9 shows the speeds of the engine and electric motor on the FTP-75 cycle. We see that the two speeds are similar. This is because in simulations of conventional and hybrid vehicles, the engines are used in the speed range between idle speed and 4000 rpm. This means that the maximum speeds of the ICE and the EM are close to each other.

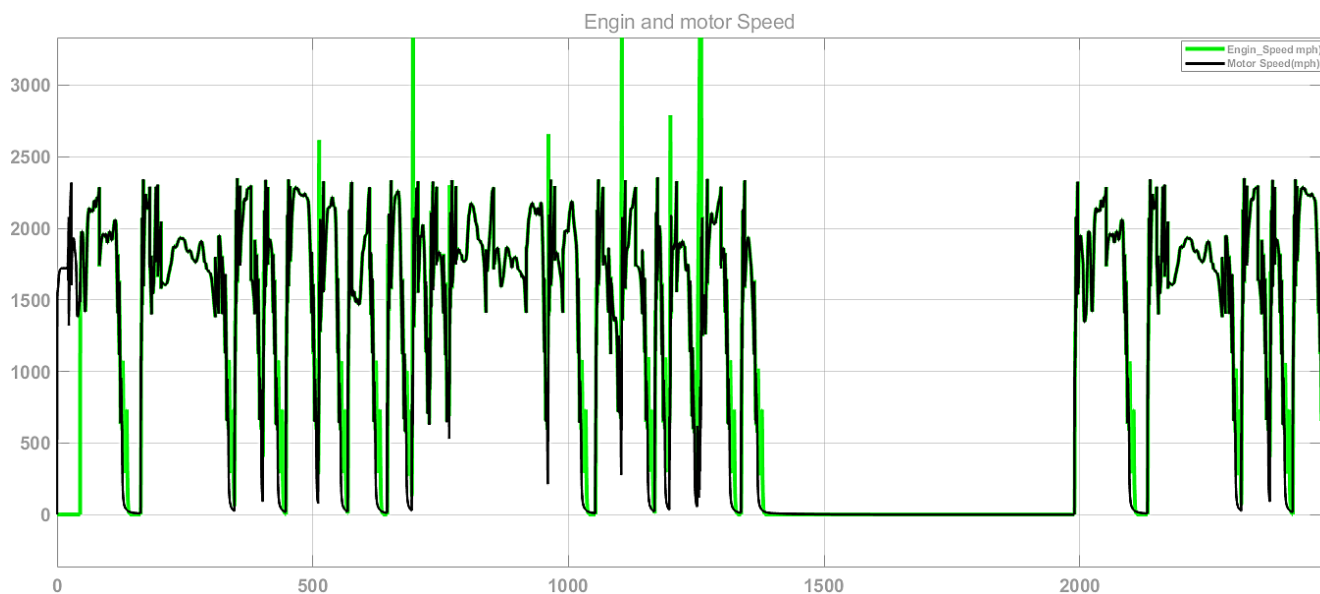


Figure 9. Speeds of the thermal and electric motors.

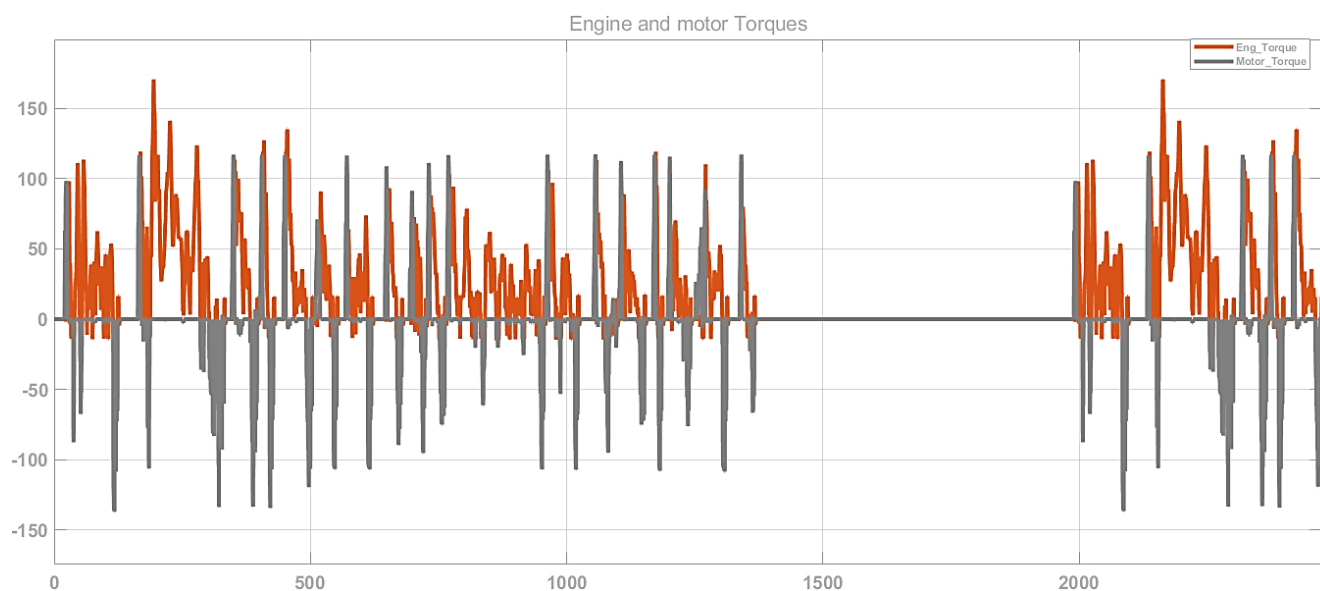


Figure 10. Torques of thermal and electric motors.

Figure 10 shows the evolution of the torques of the two motors. The vehicle starts in electric mode. This mode is maintained until the energy available in the battery cannot

meet the driver's demand. The engine is thus put into operation. Acceleration corresponds to a high demand for torque and therefore activated thermal engine.

There are three operating zones of the two engines corresponding to the different driving modes.

The first zone is the low torque demand zone (low speeds). This is the operating zone in all-electric mode.

The second zone is the zone of medium and high torque demands with battery charge. However, the energy available in the battery cannot cover the torque demand. This is the operating zone in hybrid mode where the torque at the wheel is the combination of the torques of the two engines.

The third zone is the zone of high acceleration and very low battery charge. Thus, only the heat engine provides traction

for the vehicle.

Negative values of electric motor torque illustrate the operating zones of the electric motor in generator mode. This is energy recovery mode.

Figure 11 presents the evolution of battery current, state of charge and fuel economy with an initial SOC of 40%.

At start-up a low power requirement arises, which is provided only by the electric motor. Later (120 to 150 s), the demand for power, after driving in electric mode, the battery being at its minimum, the electric chain can only provide very little electrical assistance during acceleration.

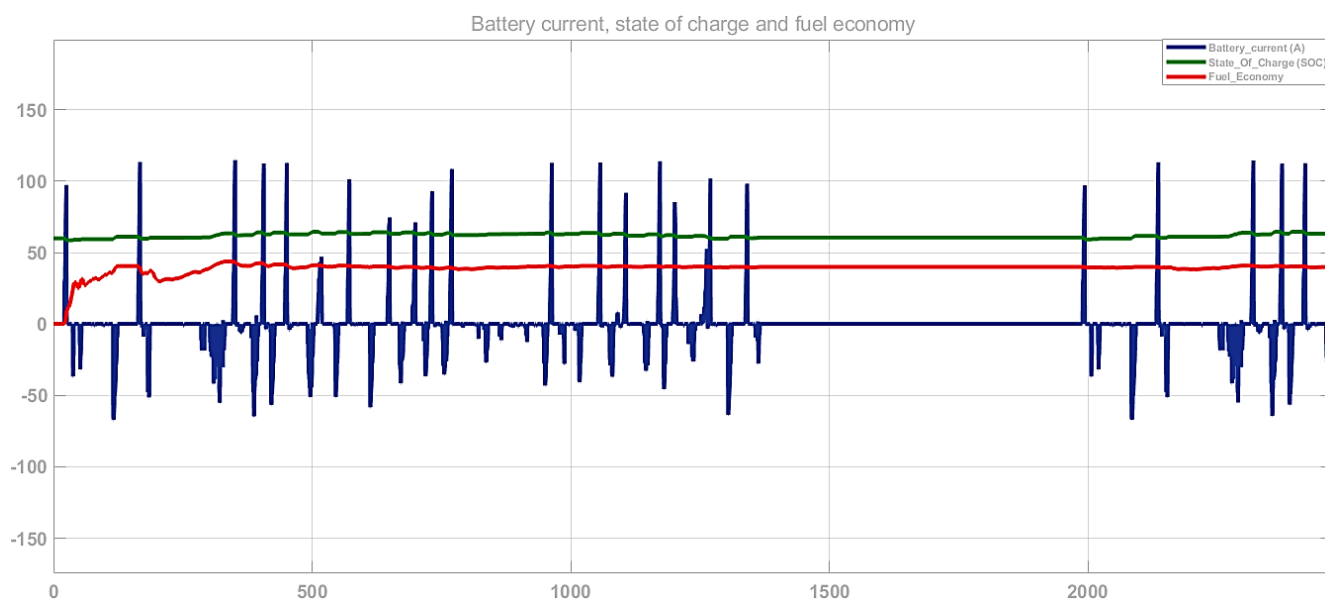


Figure 11. Battery current, state of charge and fuel economy.

Figure 12 presents the evolution of masses of hydrocarbons and nitrogen oxides.

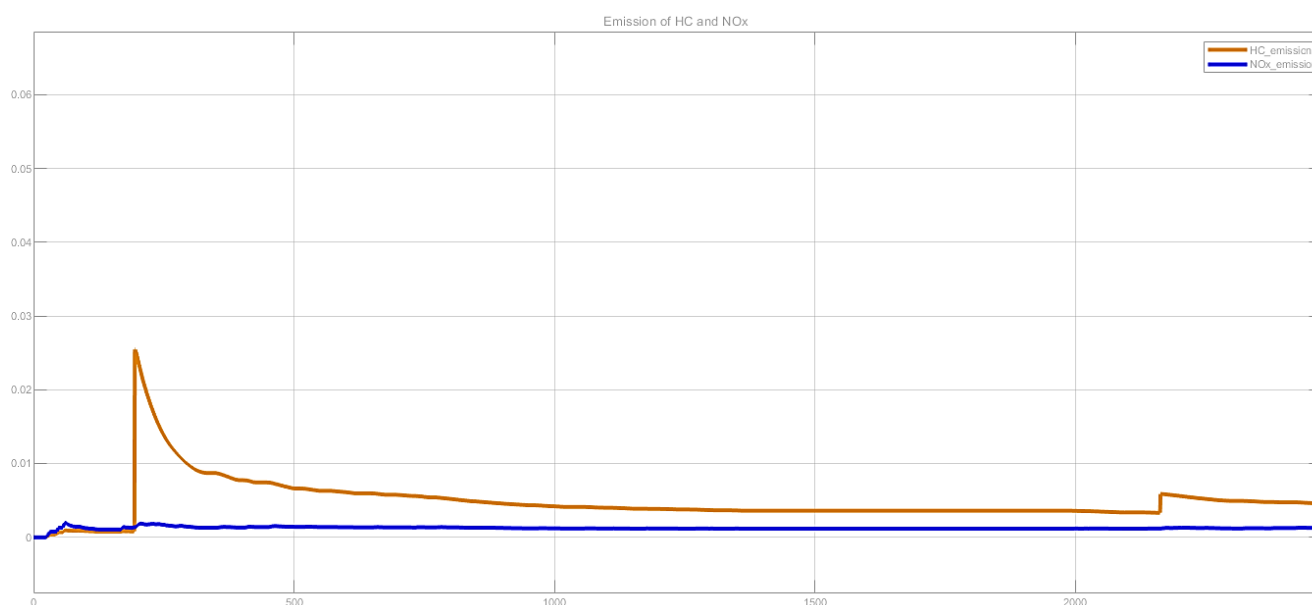


Figure 12. Estimation curves for the masses of hydrocarbons and nitrogen oxides.

The mass of NO_x is very low (0.002 g/km), while that of HC varies around 0.003 g/km, with a peak of 0.018 g/km at t=200s. Figure 13 presents the evolution of masses of carbon monoxide and dioxide.

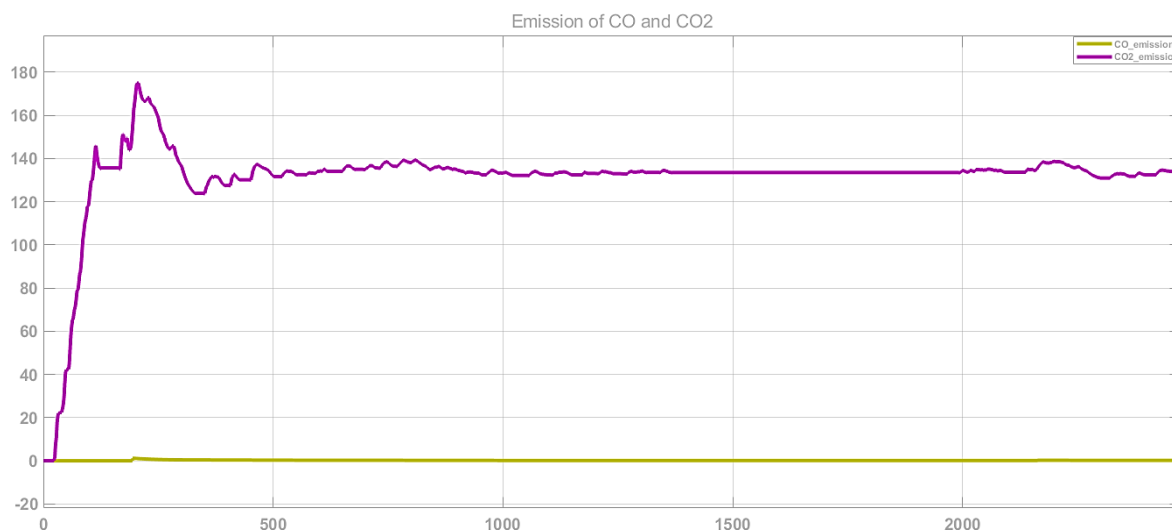


Figure 13. Estimation curves for the masses of carbon monoxide and dioxide.

The mass of CO is practically negligible, while that of CO₂ is significant and proportional to fuel consumption. Table 4 presents quantity of air pollutants emitted in g/km.

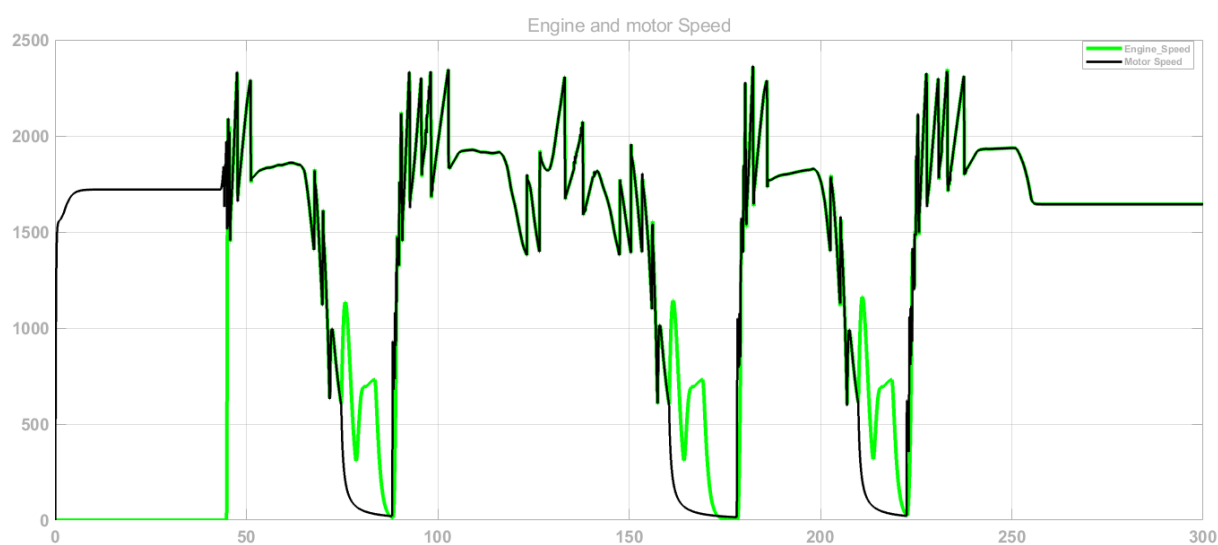


Figure 14. Speeds of the engine and electric motor.

Table 4. Quantity of air pollutants emitted in g/km.

Air pollutants	Quantity emitted in g/Km
CO ₂	130
CO	0.1
NO _x	0.03

Air pollutants	Quantity emitted in g/Km
----------------	--------------------------

HC	0.005 à 0.027
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The mass photos of CO₂ (175g/km and 142g/km) and HC (0.018g/km and 0.002g/km) are observable in 200s, 400s and 2200s.

5.2. Simulation Results with Driving Cycle Classes

Figure 14 presents the evolution of Speeds of the thermal

and electric motors.

Figure 15 presents the evolution of torques of thermal and electric motors.

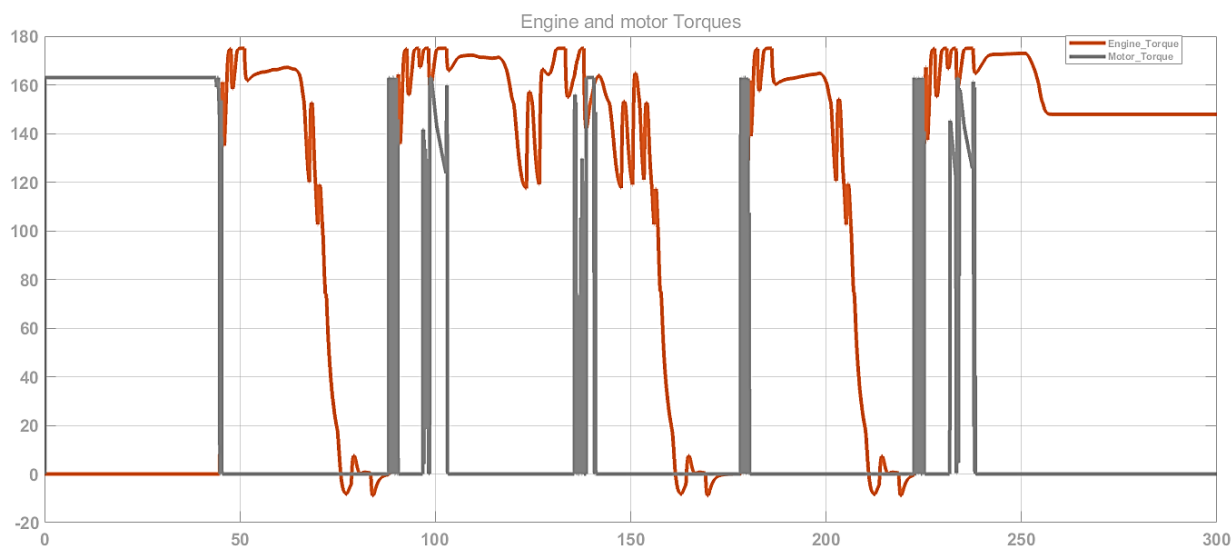


Figure 15. Torques of engine and electric motor.

The vehicle starts in pure electric mode and travels for a certain distance. The battery charge gradually decreases until it cannot meet the power demand. The internal combustion engine is then activated.

There are three operating modes:

Electric mode: Only the electric motor provides the required torque.

Internal combustion mode: The required torque is equal to the internal combustion engine torque.

Hybrid mode: The required torque is the combination of the torques of the two engines.

Figure 16 presents the evolution of the state of Battery current, state of charge and fuel economy.

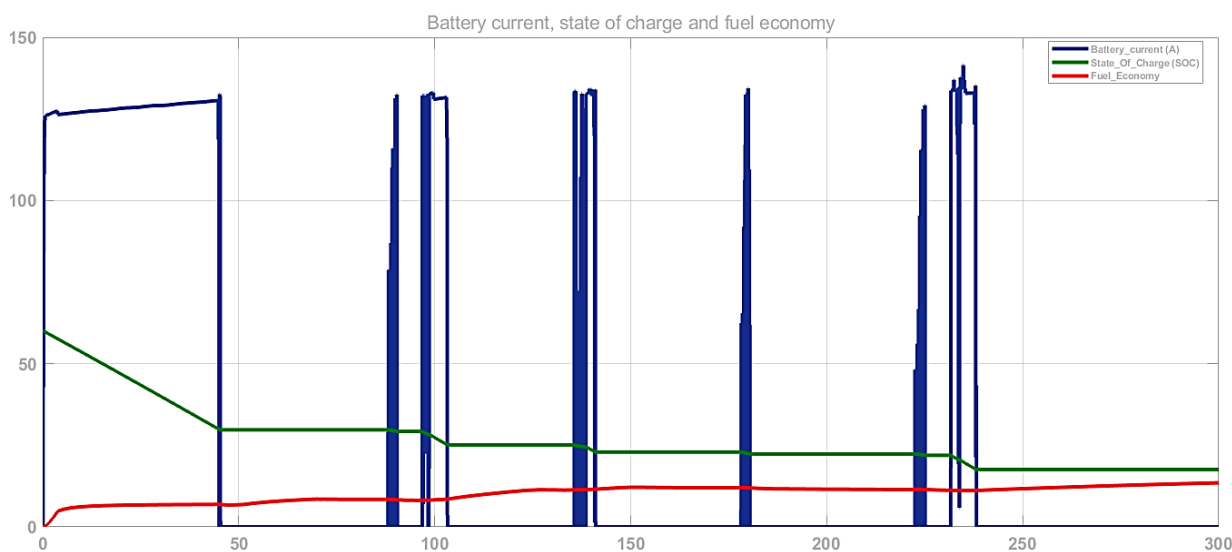


Figure 16. Battery current, state of charge and fuel economy.

The current increases at startup, which results in a significant increase in fuel economy. Thermal mode degrades fuel economy.

Figure 17 presents the evolution of masses of carbon monoxide and dioxide.

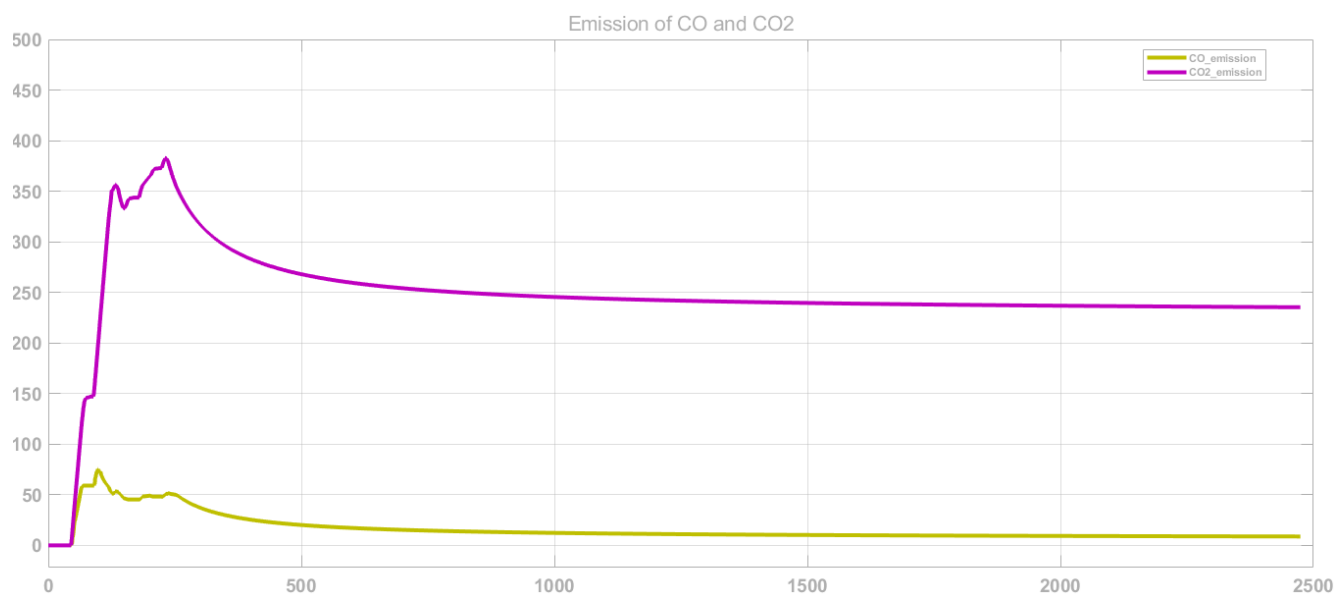


Figure 17. Estimation curves for the masses of carbon monoxide and dioxide.

Figure 18 presents the evolution of masses of hydrocarbons and nitrogen oxides.

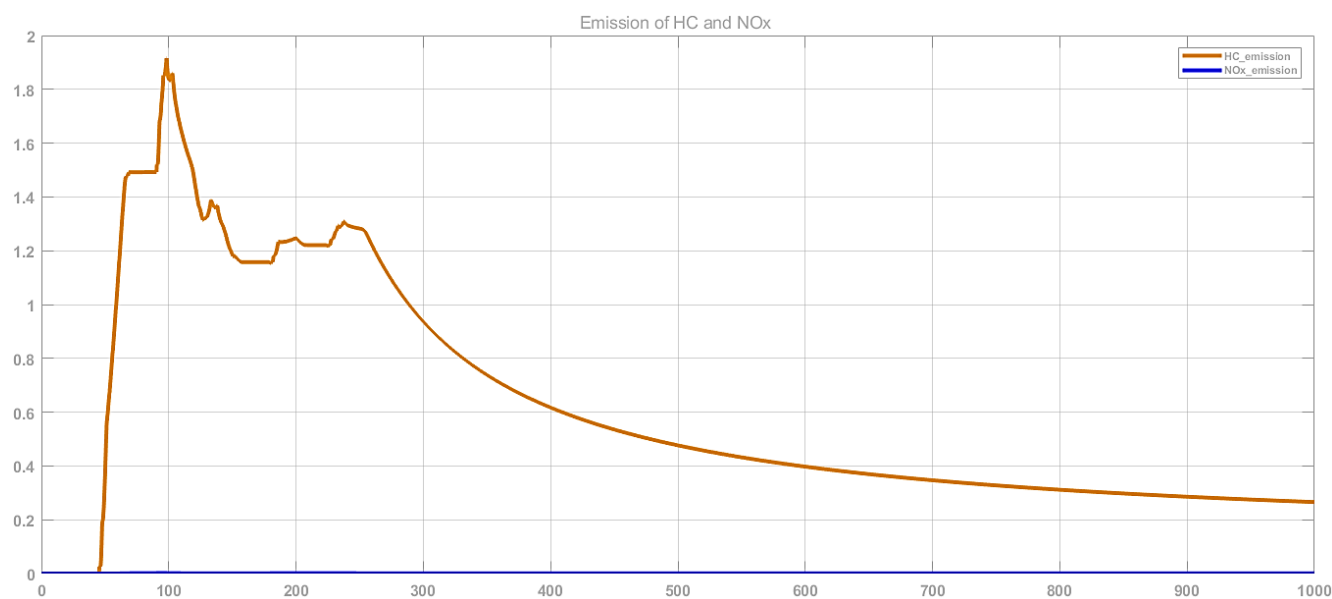


Figure 18. Estimation curves for the masses of hydrocarbons and nitrogen oxides.

Table 5 presents quantity of air pollutants emitted in g/km.

Table 5. Quantity of air pollutants emitted in g/km.

Air pollutants	Quantity emitted in g/Km
CO ₂	230
CO	12
NO _x	0.001

Air pollutants	Quantity emitted in g/Km
HC	0.2 à 1.85

5.3. Analysis

Initially, the vehicle starts and operates in electric mode, exclusively. Over a long period of time, the battery alone cannot provide the necessary energy for traction of the vehicle, and therefore the thermal engine is activated, Thus

the vehicle operates in hybrid mode. Later on, the vehicle switches exclusively into the thermal mode because the energy in the battery becomes below the limit of its operating level.

When it is operating, the electric motor develops a resistive torque in case of deceleration, dismounting or regenerative braking; hence working in generator mode. The recovered kinetic energy is stored in the battery.

Clearly, in electric mode, it can be observed a sharp improvement in terms of fuel economy. When the system switches into thermal mode, the fuel economy gets degraded.

This means that the approach employed in this paper leads to a substantial reduction in terms of fuel consumption, showing a fuel savings of around 40% for FTP-75 and 13% for the class cycle.

6. Conclusion

This paper investigated the effect of ECMS algorithm on hybrid electric vehicle. The work mainly focused on energy management using the aforementioned strategy on that type of vehicle. The performance of that approach was evaluated through extensive simulations. The simulation results showed the potential of the strategy for optimizing the vehicle's energy consumption over a given speed cycle.

The average fuel savings achieved by the A_ECMS Strategy are 40% for FTP-75 and 13% for the class cycle.

The difference in terms of fuel economy between the FTP-75 and the class cycles is mainly due to the fact that the class cycle includes numerous roads conditions such as: flat road, bush, highway, and urban road, and also considers many driving conditions (45 cycles).

The work also estimated the quantity of atmospheric pollutants including CO₂, CO, HC, and NO_x emitted by the vehicle over time. The average quantity of CO₂ emitted is 30g/km which is close to the value given in the literature (25g/km) for FTP-75 while it is 230 g/km for the class cycle against 246 g/km given in the literature [27, 31].

Adapting the equivalence factor is essential to guarantee the robustness of the SOC trajectory monitoring. It is this adaptation that determines the overall performance of the strategy on the journey.

Abbreviations

A_ECMS	Adaptive Equivalent Consumption Minimization Strategy
CO ₂	Carbon Dioxide
CO	Carbon Monoxide
DC/AC	Direct Current/Alternative Current
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimization Strategy
EM	Electric Motor

FTP	Federal Test Protocol
GA	Genetic Algorithms
HC	Hydrocarbon
LHV	Low Heat Value
NO _x	nitric oxide
PMP	Pontryagin Maximum Principle
PSO	Particle Swarms Optimization

Author Contributions

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Conflicts of Interest

The authors declare no conflicts of interest.

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