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STATE OF RESEARCH ON THE STRATEGY FOR MINIMIZING EQUIVALENT CONSUMPTION FOR SOLVING THE PROBLEM OF OPTIMAL CONTROL OF HYBRID VEHICLES

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ABSTRACT
Long considered essential in our lifestyles, the automobile vehicle is today at the heart of a multitude of nuisances including atmospheric pollution, the release of greenhouse gases and the depletion of fossil fuels. Faced with these harmful effects, research efforts are continuing to accommodate modern transport needs and meet anti-pollution regulations. It is therefore necessary to develop alternative forms of transport. It is in this context that research is focusing on the development of hybrid vehicles. A hybrid vehicle is powered by two motors (electric motor and thermal engine powered by two energy sources (the fuel tank and the battery). It is therefore necessary to properly manage the distribution of power flows between the thermal engine and the electric motor in order to reduce the vehicle's fuel consumption. The role of the energy management system is to choose at any time the best distribution of power between the different energy sources so as to minimize fuel consumption and pollutant emissions The energy performance of a hybrid vehicle depends mainly on the performance of this system. This article presents a state of research on the strategy of minimizing equivalent consumption. The main objective of this method is to minimize the fuel consumption of the vehicle and reduce the relative emission of harmful emissions.

KEYWORDS: Hybrid electric vehicle, Modeling, Control strategy, Energy management, ECMS

1. INTRODUCTION
Faced with the future shortage of fossil resources and environmental issues, there is a need to accommodate modern travel needs to meet anti-pollution standards put in place by governments to limit harmful emissions. It is with this in mind thatcar manufacturers committo 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 reproduction of electrical energy by recovery of kinetic 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 short autonomy compared to the thermal vehicle and the cost [1, 2, 3, 4].
Indeed, after a single complete battery recharge, most electric vehicles on the market have less than 500 km of range, while thermal vehicles with a full fuel tank have a range of around 1000 km.
The other weak point is the recharge time of electric vehicle batteries. Battery recharge time depends on the electrical power of the charging source. Half an hour of charging gives a respective range of 27 km for an 11 kW

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domestic socket, 136 km for a 50 kW public charging station and 270 km through a 120 kW super charger. On the other hand, refueling for at least 500 km of autonomy can be done in a few minutes [5].

While waiting for a generation of electric vehicles with batteries allowing 1000 km of autonomy and charging technologies in less than 5 minutes, the hybrid vehicle is an ideal solution for this transition phase from thermal vehicles to electric vehicles. The presence of two motors (an electric motor and a thermal engine) and two energy sources requires the presence of a controller which will simultaneously control the two motors. In terms of consumption, the performance of a plug-in hybrid electric vehicle depends largely on the performance of this controller. The specificity of plug-in hybrid electric vehicles lies in recharging the battery through a mains electrical outlet, at a public terminal or through regenerative braking. Which requires an internal charger allowing this recharging. This makes the design of the energy management system more complex [4, 5, 6].

2. FORMULATION OF THE OPTIMAL CONTROL PROBLEM

Since the objective of energy management strategies is to maximize the energy available in the battery and minimize fuel consumption, the dynamic system considered is the battery and its state variable is the state of charge noted x.

$$x(t) = SOC(t) = \frac{q_b}{Q_{\max}} \quad (1)$$

The current leaving the battery being the opposite of the current entering, its expression is given by the equation 2.

$$-I_b = \frac{dq_b}{dt} \quad (2)$$

The amount of charge stored at each moment in the battery is given by the equation 3.

$$q_b = -\int_0^t I_b dt \quad (3)$$

$$SOC(t) = \frac{-I_b t}{Q_{\max}} \quad (4)$$

The equivalent battery diagram allows you to express the nominal voltage of the battery.

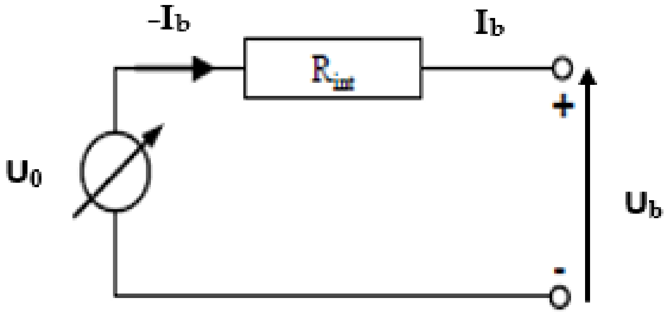

Figure 1: Equivalent electrical diagram of the battery [3]

$$U_b = U_0 - I_b R_{\text{int}} \quad (5)$$

$$I_b = \frac{U_0 - U_b}{R_{\text{int}}} \quad (6)$$

We obtain the expression of the state of charge according to the characteristics of the battery.

$$SOC(t) = \frac{-(U_0 - U_b)t}{R_{\text{int}} Q_{\max}} \quad (7)$$

We define a penalty factor based on the instantaneous SOC making it possible to maintain the SOC around the target SOC and between its limit values SOCmax and SOCmin. This penalty factor This penalty factor is assigned to the consumption of electrical energy in order to secure the battery. The target SOC is specified based on the efficiency of the HV battery.
The minimization function is the fuel consumption over a speed cycle.

$$J_{tot} = \int_{t_0}^{t_f} \dot{m}_c (u(t), T(t), \omega(t))\, dt \quad (8)$$

Where is the instantaneous fuel consumption.
The minimization problem is also subject to several constraints

- The terminal constraints on the u command, denoted umin and umax due to the saturations of the actuators [2] ;

$$\begin{cases} \omega_{\text{thmin}} \le \omega_{th} \le \omega_{\text{thmax}} \\ \mathrm{T}_{\text{tmin}} \le T_{th} \le T_{\text{tmax}} \\ \omega_{\text{emin}} \le \omega_e \le \omega_{\text{emax}} \\ \mathrm{T}_{\text{emin}} \le T_e \le T_{\text{emax}} \end{cases} \quad (9)$$

- The state of charge of the battery which must not exceed a certain threshold to ensure battery safety [2].

$$X(t_f) = X(t_0) + \Delta X$$

The minimization problem is therefore formulated by :

$$J_{tot} = \min \int_{t_0}^{t_f} \dot{m}_C (u(t), T(t), \omega(t))\, dt \quad (10)$$

Under the constraints:

$$\begin{cases} \omega_{\text{thmin}} \le \omega_{th} \le \omega_{\text{thmax}} \\ \mathrm{T}_{\text{tmin}} \le T_{th} \le T_{\text{tmax}} \\ \omega_{\text{emin}} \le \omega_e \le \omega_{\text{emax}} \\ \mathrm{T}_{\text{emin}} \le T_e \le T_{\text{emax}} \\ X(t_f) = X(t_0) + \Delta X \end{cases} \quad (11)$$

3. SOLVING THE ENERGY MANAGEMENT PROBLEM OF HYBRID VEHICLES

In a hybrid vehicle, torque to the wheels is provided by one or both energy chains. The objective of energy management is to find, on a given journey, the distribution of power flows, between the two traction chains, which minimizes fuel consumption while guaranteeing a given final state of charge of the battery. Algorithms for solving this problem are called "power management strategies". These algorithms are classified into three categories namely rule-based methods, optimization methods and methods based on artificial intelligence (figure 2).

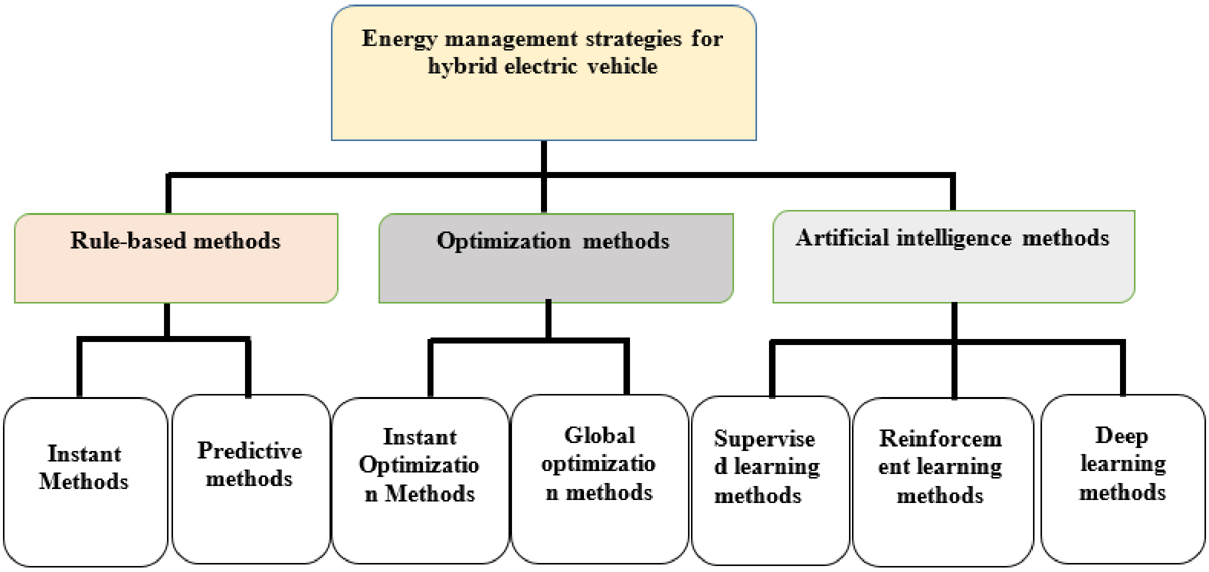

Figure 2 : Classification of energy management strategies [3, 11]

3.1. Rule-based strategies

These are strategies based on predefined rules of thumb allowing an action to be carried out from a certain fixed threshold. These strategies come from the experiences acquired by experts on the behavior of the different components of the powertrain. In general, the operating point of the thermal engine is fixed in its maximum efficiency zone and the driver's power demand is supplemented by the electric motor according to the state of charge of the battery.

Rule-based methods are either instantaneous or predictive [2, 3].

In instantaneous methods, the control of the vehicle depends solely on its current state while in predictive methods, the control comes from the evaluation of a series of commands on a future environment.

The rule-based methods are closely linked to the parameters of the energy chain components and the rolling profile. These strategies include the thermostat method, the power monitoring method, the state machine, fuzzy logic, etc.

The advantages and disadvantages of these strategies are presented below [2].

Benefits

- Speed and simplicity of implementation
- Less intensive in calculation time and memory
- Guarantee of stable and invariable operation

Disadvantages

- Based on the experimental knowledge of experts and are only valid within the area of this expertise
- No longer meeting current expectations of energy management strategies
- Very limited and are not optimal in general

3.2. Optimization methods

These are methods for modeling a system and formulating the optimization problem in order to find solutions. They use mathematical tools to find the optimal operating sequence of a system through a cost function to be minimized.

The cost function is generally the total fuel consumption over a speed cycle.

Optimization methods are classified according to whether they can be embedded in real time (online strategies) or intended only for simulation (global optimization methods). Offline global optimization methods are based on a priori knowledge of the speed profile. They are therefore intended only for simulation, but are the only ones to guarantee global optimality of the control up to modeling errors. Nevertheless, their results can be used to develop online methods.

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These methods include Dynamic Programming (DP, GA genetic algorithms), simulated annealing, particle testing (PSO), Stochastic Dynamic Programming (SDP) [2, 3, 9].
Online optimization methods are strategies that can be implemented on real vehicle computers. These are instantaneous optimization methods allowing, at any moment, to evaluate the constraints and define the operating points of the components of the vehicle's powertrain. Above all, they make it very easy to exploit the predictive data available.
Among these methods we can cite the Equivalent Consumption Minimization Strategy (ECMS), the Pontriagin Maximum Principle (PMP), the predictive control model (MPC) [12, 13].

3.3. Artificial intelligence methods

With the development of artificial intelligence, energy management strategies increasingly integrate machine learning algorithms. These algorithms allow the energy management system to learn to adapt to driving conditions in order to optimize energy distribution in real time.

Benefits

- tackles the problem head on.
- Can be used to derive applicable online ordering strategies.
- very useful for adjusting other rule-based management strategies

Disadvantages

- modeling and resolution difficulties
- Requires knowledge of all driving profile information (road and route conditions)

Expensive in calculation time and memory

4. MINIMIZATION OF EQUIVALENT CONSUMPTION (ECMS)

Having become one of the main directions in the research of energy management strategies, ECMS is a local optimization algorithm first developed in 1999 by Paganelli [21].
In ECMS strategies, the optimization problem amounts to calculating an equivalence factor making it possible to maintain the state of charge of the battery around a target reference value. This equivalence factor is a conversion factor between electrical energy and thermal energy. It makes it possible to bring energy consumption into the same energy space in order to determine the optimal control variables [14, 15, 18, 21].
Several variants of the CHMS exist depending on how the equivalence factor is evaluated and whether or not available external information is integrated. This information may be traffic information, driver information, or vehicle information. In the non-adaptive variants (Non Adaptive ECMS) the values of the equivalence factor are chosen a priori while the adaptive variants (Adaptive ECMS) allow the equivalence factor to be updated at each moment of the journey. Equivalence factor values are selected based on prediction levels of future driving conditions. Telemetry ECMS uses information provided by the navigation system to update the equivalence factor. In offline ECMS methods, the equivalence factor is optimized by another optimization algorithm such as PSO, GA.
This optimization method involves evaluating 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 component yields may differ between operating areas, this methodology is valid for average value assessments [19, 20, 21, 22].
In ECMS policies, the batteryis considered an auxiliary fuel tank. This makes it possible to choose at any time the control variables making it possible to minimize the total energy taken from the two reservoirs via an equivalence factor which makes it possible to convert the electrical energy into mechanical energy to reduce 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 time t. This corresponds to a quantity of electrical energy taken from the battery at that moment. This quantity of energy must be returned to the battery at the higher time t'>t. At this moment, the quantity of fuel consumed must ensure the traction of the vehicle and the recharging of the battery [23].

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The second case corresponds to the storage of electrical energy in the battery (recharging the battery) at a time t. At the higher time t' > t, this stored energy will contribute to vehicle traction and fuel economy [23].

The energy distribution of the hybrid vehicle according to the operating mode is illustrated in Figure 3.

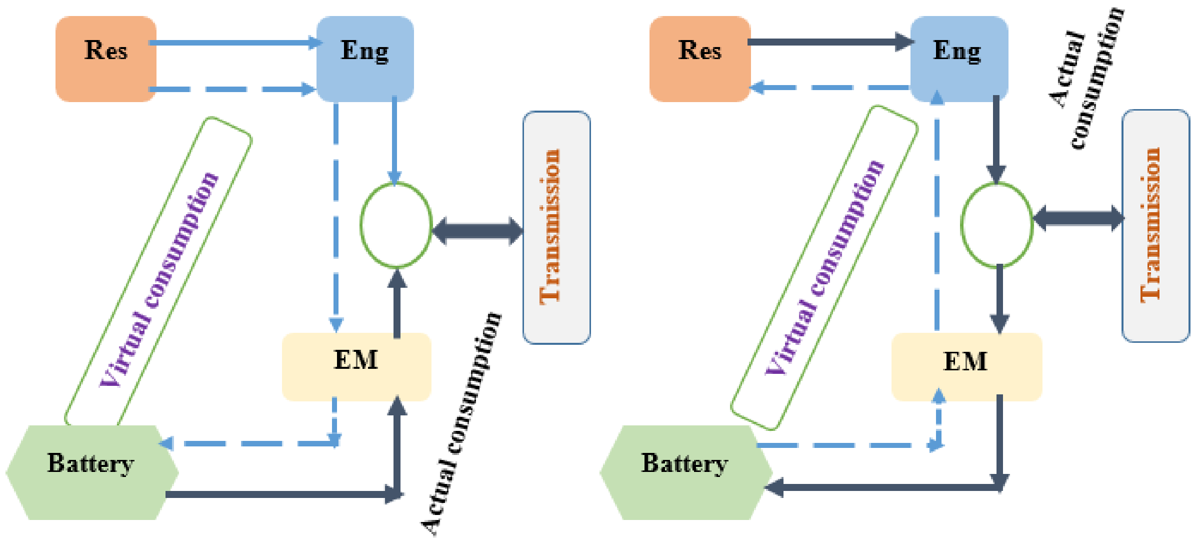

Figure 3 : Energy distribution of the hybrid vehicle

4.1. ECMS Algorithm Expressions

The ECMS algorithm has two expressions. The first is the original expression proposed by Paganelli. This is illustrated by equation 12.

$$\dot{m}_{eq}(t) = \dot{m}_c(t) + \dot{m}_b(t) \quad (12)$$

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

Instantaneous consumption of fuel and electrical energy is expressed according to the characteristics of the shareholders.

$$\dot{m}_c(t) = \frac{P_{th}(t)}{\eta_{th}(t)Q_{LHV}} = \frac{P_r(t)u(t)}{\eta_{th}(t)Q_{LHV}} \quad (13)$$

$$\dot{m}_b(t) = \frac{s}{Q_{LHV}} P_b(t) = \frac{s}{Q_{LHV}} P_r(t)(1-u(t)) \quad (14)$$

$$\dot{m}_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t)Q_{LHV}} + \frac{s(t)P_b(t)}{Q_{LHV}} \quad (15)$$

$$\dot{m}_{eq}(t) = \frac{1}{\eta_{th}(t)Q_{LHV}} P_r(t)u(t) + \frac{s}{Q_{LHV}} P_r(t)(1-u(t)) \quad (16)$$

Where Pth(t) is the power of the heat engine, Pr(t) the required power
u(t) the vector of control variables, Pb(t) the power of the battery, QLHV the minimum released by the combustion of the fuel, ηth(t) the efficiency of the thermal engine, Pb(t) the power of the battery , s(t) the equivalence factor

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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 makes it possible to delimit the SOC between the two values and its maintenance around a target SOC. This SOC target should be specified based on battery efficiency.

$$p(SOC) = 1 - \left(\frac{SOC(t) - SOC_{cible}}{0.5(SOC_{\max} - SOC_{\min})} \right)^{a} \quad (17)$$

$$\dot{m}_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t) Q_{LHV}} + \frac{s(t) P_b(t)}{Q_{LHV}} * p(SOC) \quad (18)$$

$$P_{eq} = \dot{m}_{eq} * Q_{LHV} \quad (19)$$

$$P_{eq}(t) = \frac{P_{th}(t)}{\eta_{th}(t)} + s(t) P_b(t) * p(SOC) \quad (20)$$

$$\dot{m}_{eq}(t) = \frac{1}{\eta_{th}(t) Q_{LHV}} P_r(t) u(t) + \frac{s}{Q_{LHV}} P_r(t)(1 - u(t)) \quad (21)$$

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

$$P_{th} = T_{th} \omega_{th} \quad (22)$$

$$\eta_{th} = \frac{P_{th}}{P_c} \quad (23)$$

$$P_c = m_f H_{PCI} \quad (24)$$

$$P_{th}(t) = u^*(t) P_r(t) \quad (25)$$

$$P_b(t) = (1 - u^*(t)) P_r(t) \quad (26)$$

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

The required power is obtained by establishing the balance which acts on the vehicle. The different forces to which the moving vehicle is subjected (traction force Fr, gravity force Fg, rolling resistance Froul, Aerodynamic Drag Fa), are represented in Figure 4.

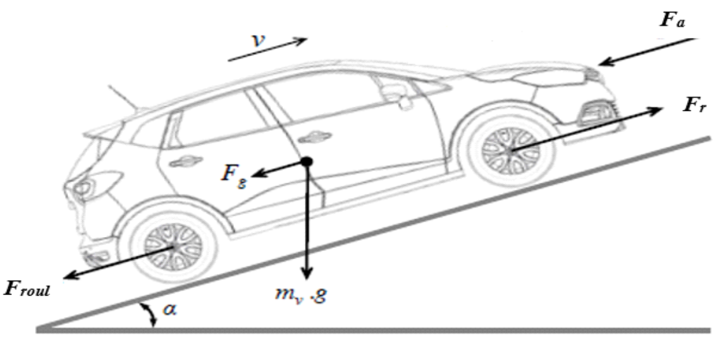

Figure 4 : Forces applied to the vehicle [3]

The equation which governs the longitudinal dynamics of the vehicle, resulting from the application of the fundamental principle of dynamics (Newton's second law) is:

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$$m\frac{d\,v(t)}{dt} = F_r(t) - F_{resist}(t) \qquad (27)$$

The vehicle's traction force requested by the driver is:

$$F_r = F_a + F_{roul} + F_g + F_{ac} \qquad (28)$$

By expressing these forces as a function of the characteristics of the vehicle and its environment, we obtain:

$$F_r = mgf\cos\alpha + mg\sin\alpha + \frac{1}{2}C_D A v^2 + F_d + m\frac{dv}{dt} \qquad (29)$$

The power requested by the driver expressed as a function of the force required and the speed of the vehicle is:

$$P_r = \left(mgf\cos\alpha + mg\sin\alpha + \frac{1}{2}C_D A v^2 + F_d + m\frac{dv}{dt}\right)v \qquad (30)$$

Where f is the rolling resistance coefficient, η the overall efficiency of the transmission system, α the slope, CD the air resistance coefficient, A the frontal wind surface, σ the mass factor which helps convert the rotational inertias of the rotational elements in translation.
In the ECMS algorithm, the total consumption is the total equivalent consumption, the equation ... becomes:

$$J_{tot} = \min\int_{t_0}^{t_f} \dot{m}_{eq}(P_r(t), u(t), s, t)\,dt \qquad (31)$$

$$J_{tot} = \min\int_{t_0}^{t_f} \dot{m}_c(P_r(t), u(t)s, t) + \dot{m}_b(P_r(t), u(t)s, t)]dt \qquad (32)$$

Under the constraints :

$$\begin{cases} u_{\min} \le u^*(t) \le u_{\max} \\ s_{\min} \le s \le s_{\max} \\ t_0 \le t \le t_f \end{cases} \qquad (33)$$

The Hamilton equation implements the Hamiltonian allowing the control variables to be derived.

$$H(P_r(t), u(t)s, t) = \dot{m}_c(P_r(t), u(t), s, t) + \dot{m}_b(P_r(t), u(t), s, t) \qquad (34)$$

The optimal solution of the control variables is:

$$u*(t) = \arg\min H(P_r(t), u(t), s, t) \qquad (35)$$

$$P_{b\min} \le P_b \le P_{b\max} \qquad (36)$$

$$P_{th\min} \le P_{th} \le P_{th\max} \qquad (37)$$

meq(t): Total instantaneous equivalent consumption (g/s),
mc(t): Fuel consumption (g/s),
mb(t): Equivalent consumption of electrical energy
Pth(t): Power of the thermal engine
Pr(t): Power required
u(t): Control variables
Pb(t): Battery power
QLHV: Minimum heat released by fuel combustion
η(t): efficiency of the heat engine
Pb(t): Battery power
Another expression of ECMS can be deduced from the Pontriagin Minimum Principle PMP under certain conditions.

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$$H(x(t),u(t),\lambda(t),t) = L(x(t),u(t),t)+\lambda(t)f(x(t),u(t)) \quad (38)$$

$$H(x(t),u(t),\lambda(t),t) \geq H(x(t),u*(t),\lambda(t),t) \ \forall u \neq u*, t \in [t_0, t_f] \quad (39)$$

$$\dot{\lambda}(t) = \frac{\partial}{\partial x} H(x(t),u(t),\lambda(t),t) \quad (40)$$

$$u*(t) = \arg\min\{H(x(t),u(t),\lambda(t),t)\} \quad (41)$$

4.2. ECMS algorithm based on different information sources

The equivalence factor is the most important parameter of the ECMS algorithm. It represents the efficiency of energy conversion of energy sources from one to another. The determination of this equivalence factor depends on several elements including the components of the energy transmission chains, the driving conditions, the driving profile, etc. As a result, there are several variants of the ECMS algorithm depending on the information sources enabling this equivalence factor to be determined. The diagram below provides a classification of ECMS algorithms according to information sources [11, 21].

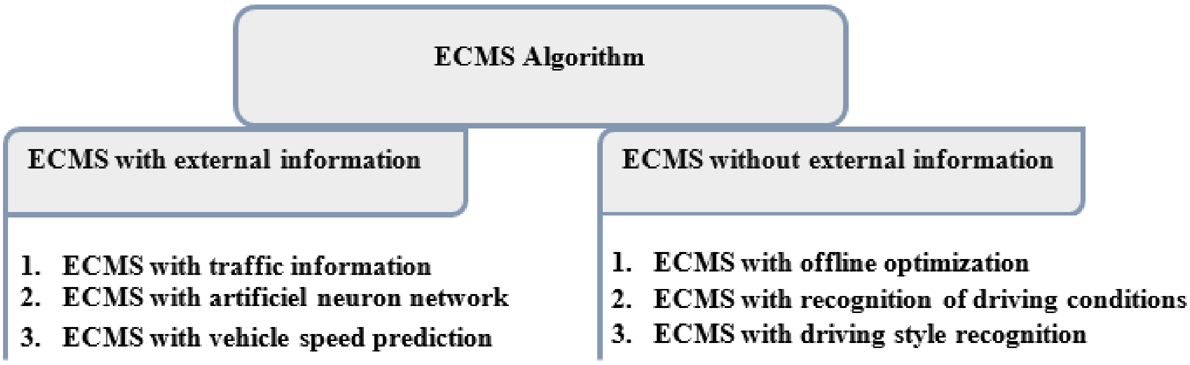

Figure 5 : Classification of ECMS energy management strategies [11, 21]

4.3. ECMS with external information

Advances in communication technologies between vehicles and road infrastructure allow vehicles to acquire information about routes and traffic conditions. This information is used to develop new approaches to the ECMS algorithm. These ECMS methods with external information are classified into three categories including ECMS with traffic information, ECMS with artificial neural networks and ECMS with vehicle speed prediction [21].

4.4. ECMS with traffic information

The ECMS method with traffic information is an ECMS algorithm based on the prediction of road conditions and road traffic. CES information is typically mileage information, road terrain information, and navigation information. The difference between ECMS with traffic information and other prediction strategies (ECMS with road condition prediction, ECMS with driving style prediction and ECMS with speed prediction is the prediction period. The prediction period is important for the ECMS with road information (kilometers) while it is low for other ECMS prediction strategies (a few seconds), which favors the improvement of the degree of freedom and therefore the optimization of the vehicle's energy consumption. , this length of the prediction period gradually deteriorates the robustness of ECMS [21].

4.5. ECMS with artificial neural networks and traffic information

Artificial neural networks are combined with ECMS algorithms to optimize the energy consumption of hybrid vehicles. They are used in particular to determine the optimal value of the equivalence factor from a large quantity of data. These data are generally the characteristics of the heat engine [29], the characteristics of the road [21], the characteristics of the environment [24] and the driver that can be recorded during real journeys. Obtaining training data from neural networks to extract optimization parameters proves to be the most difficult task. However, they can also be generated from normalized speed cycles [18].

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In [30], the authors developed comparisons between artificial neural networks and dynamic programming in simulations. Neural networks gave good performance to be compared with dynamic programming which is a reference strategy.

4.6. ECMS with vehicle speed prediction

Predicting the speed of hybrid vehicles in adaptive strategies for minimizing equivalent consumption plays an important role in updating the equivalence factor. By predicting short-term speed with an appropriate approach based on vehicle data and driving conditions, the energy management algorithm intelligently adapts the equivalence factor value to optimize fuel economy . of the vehicle. There are two speed prediction approaches to determine the equivalence factor of the A_ECMS algorithm. In one of these approaches, a reference SOC of the battery is set and the equivalence factor is adjusted to follow the reference SOC initially set [21, 27, 31]. In the other approach, the value of the equivalence factor is calculated from the range of values of the predicted speed or from the estimate of the energy consumption of the vehicle. The most used algorithms are artificial neural networks (Radial basis function networks (RBF), long short-term memory networks (LSTM)) [18], support vector machines (SVM) etc.

In [32], the authors developed an adaptive ECMS algorithm using artificial neural networks. The equivalence factor is calculated by adopting the driving profile to predict the vehicle speed.

In the work presented in [33], the authors used the predicted speed curve as input to an RBF neural network to predict the slope of the reference SOC curve.

In [34], the authors developed a short-term vehicle speed prediction algorithm to calculate the range of the maximum equivalence factor.

4.7. ECMS with prediction of environment and driving conditions

Shilin Pu et al. [35], proposesa strategy for minimizing equivalent consumption based on perception of the environment for parallel plug-in hybrid vehicles. In This strategy, traffic characteristics information is obtained from an intelligent traffic system. This information makes it possible to adopt the equivalence factor of the ECMS strategy. The intelligent traffic system is based on a graphical convolutional network. The results obtained showed that the developed strategy makes it possible to achieve 7.25% fuel savings compared to the classic ECMS strategy.

Chunna Liu et al. [36] made a comprehensive analysis of the energy management strategies of plug-in hybrid vehicles based on the recognition of driving conditions. These strategies use driving information to optimize target parameters in online and simulation control. With the progress of artificial intelligence technologies, several intelligent methods based on are increasingly used in solving energy management problems based on the recognition of driving conditions including neural networks, deep learning [37] and by reinforcement [38]. The various results showed good fuel economy.

4.8. ECMS with vehicle state of charge prediction

M. Piras et al. [39], propose an ECMS strategy based on speed prediction and the planning the trajectory of the battery state of charge. Vehicle speed is predicted from driving profile data. ThereNeural network-based battery state-of-charge trajectory planning is done using the information provided by the mapping to plan a discharge trajectory from a final SOC of 30% to start of each trip for different driving cycles with initial SOC values.

Simona Onori et al.[40], carried out a comparative simulation analysis of three methods of adapting the equivalence factor of the ECMS strategy for a parallel hybrid vehicle. The equivalence factor is appreciated by open loop around a reference value by evaluating the error between the target SOC and the instantaneous SOC. The results obtained prove the better performances of the three adaptation methods and the ECMS strategy.

4.9. ECMS without external information

The ECMS strategy without external information is used in the context of offline optimization where ECMS is combined with the global optimization algorithms.

Global optimization methods are valid when the vehicle speed profile is known a priori. They are therefore reduced to use in simulation which can be used to evaluate online ordering strategies.

ECMS with offline optimization algorithms requires the exact knowledge of integral information about driving conditions. This information cannot be obtained in advance under practical driving conditions. This is what limits ECMS with offline optimization to simulations. Optimization algorithms are divided into three categories namely global optimization approaches, heuristic approaches and numerical approaches. We thus distinguish ECMS with

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heuristic approaches including GA, PSO, global optimization approaches (DP, SDP) and ECMS with numerical approaches [41, 42, 43]. However, rule-based methods and artificial intelligence methods can also be combined with ECMS and driving condition recognition or ECMS and driving style recognition [21].

5. CONCLUSION

We have presented, in this article, a state of research on the strategy of minimizing equivalent consumption. We first formulated the energy management problem of hybrid vehicles and the classification of the different categories of its resolution methods. Then, we presented the different ECMS methods with and without external information as well as the associated work.

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