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Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 2000 214: 705
DOI: 10.1243/0954407001527583

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Simulation and assessment of power control strategies for a parallel hybrid car

G Paganelli[1], **T M Guerra**[1]*, **S Delprat**[1], **J-J Santin**[1], **M Delhom**[2] and **E Combes**[2]
[1]Laboratoire d'Automatique et de Mécanique Industrielles et Humaines, University of Valenciennes, France
[2]PSA Peugeot Citroën, Vélizy-Villacoublay, France

Abstract: The aim of this paper is to propose a power control strategy for hybrid electrical vehicles. This strategy uses a fuel consumption criterion with battery charge sustaining. It is based on an instantaneous minimization of the equivalent fuel flow. Two comparisons are performed to evaluate the proposed strategy. The first one uses the loss minimization strategy of Seiler and Schröder [**1**], which appears to be realistic and efficient for real-time control. This strategy is also based on an instantaneous optimization and allows the battery state of charge to be taken into account. The second comparison is made with an optimal solution found for a given driving schedule. Although not realistic for real-time control, this solution is derived through a global optimization algorithm, the well-known simulated annealing method.

Keywords: hybrid vehicle power, control strategy, fuel consumption, energy management, power-train control

NOTATION

C	cost of the battery current change (g/s A)
E	amount of energy (W h)
ΔF	increase of total equivalent fuel flow over optimal one (g/s)
$F_e(i)$	instantaneous engine fuel consumption at sample i
$F_m(i)$	equivalent instantaneous electric motor fuel consumption at sample i
i	sample
ΔI_{batt}	difference between instantaneous battery current and the optimal one (A)
k_r	gear number
n_e	engine speed (rad/s)
n_{e_max}	maximum engine speed (rad/s)
n_{gears}	total number of gears
n_m	electric motor speed (rad/s)
n_w	wheel speed (rad/s)
N	speed cycle duration
ΔP_l	increase of total loss over the optimal one (W)
$P_l(i)$	total loss at sample i (W)
$R(k_r)$	reduction ratio of the k_rth gear, $k_r \in \{1, \ldots, n_{gears}\}$
S	sensitivity according to the loss minimization strategy (W/A)
T_e	engine torque (N m)
T_{e_max}	maximum torque on shaft engine over speed (N m)
T_m	electric motor torque (N m)
$T_{m\_min}(n_e)$	minimum negative electric shaft torques over speed (N m)
$T_{m\_max}(n_m)$	maximum positive electric shaft torques over speed (N m)
T_w	wheel torque (N m)
$X(k)$	kth solution for global optimization
ρ	speed ratio between electric motor shaft and engine shaft

The MS was received on 17 June 1999 and was accepted after revision for publication on 14 October 1999.
**Corresponding author: LAMIH, University of Valenciennes, Le Mont Houy, BP311, 59304 Valenciennes Cedex, France.*

1 INTRODUCTION

Nowadays, customers expect cars using new technologies which allow reduction in the emission of the noxious particles in the exhaust gas but without reducing the vehicle range. A first trial was made with electrical drive units, but their excessive price and short range inhibited their commercial success. A hybrid electrical

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vehicle (HEV) seems to be a good approach to this problem and is expected to give good results in terms of pollution, range and fuel consumption.

A hybrid powertrain consists of several energy sources and converters linked together through different mechanical or electrical parts. The driver continuously provides a wheel torque set point which has to be produced using the different motors.

Cooperation between Peugeot Citroën Recherche (PSA), Agence de l'Environnement et de la Maitrise de l'Energie (ADEME) and Laboratoire d'Automatique et de Mécanique Industrielles et Humaines (LAMIH) began in October 1996. This work has been supported by the European Funds for Regional Expansion (FEDER). The global objective is the design and optimization of a parallel hybrid powertrain. This paper is mainly focused on the control strategy problem.

In spite of an excess load of about 300 kg over the same car with an internal combustion engine (ICE), the best fuel consumption is expected from an HEV. The fuel consumption strategy is the key point to control the HEV powertrain. Because of the number of components and the different energy exchanges, this problem remains difficult.

In hybrid mode, the power for propelling the vehicle is provided partly by the engine and partly by the electric motor. This mode is expected to be less polluting and cheaper than using only the engine. The goal is to propose a method to obtain an optimal distribution of the power between the electric motor and the engine contributions. Of course, the pure electric mode is not involved.

Several papers address control strategy of HEVs, through simulation [**1**–**3**] or for real-time application [**4**]. The engine is generally used to maintain the state of charge (SOC) of the battery (charge-sustaining strategies). In some cases, the battery is only charged from a wall socket and by regenerative braking but never from the engine [**5**, **6**]. This leads to a continuous decrease of the battery's SOC.

In the present case, a fuel consumption criterion with battery charge sustaining is used. It is based on an instantaneous minimization of the equivalent fuel flow. The results here are compared with those obtained with a strategy proposed by Seiler and Schröder [**1**]. It was chosen because it uses the same criterion and appears to be realistic and efficient for real-time control.

A global optimization is also proposed, allowing an optimal solution to be reached for a given cycle. Even if the solution obtained cannot be directly used for real-time control, it can be considered as a reference to evaluate the proposed strategy. This global optimization is done using the well-known simulated annealing algorithm.

This work is clearly related to the chosen mechanical arrangement but it can be easily extended to other kinds of parallel HEVs.

2 PARALLEL HEV

HEVs combine at least two types of energy converters [**7**]. The most common version of hybrid vehicles uses an electric motor and a combustion engine. This kind of HEV can be divided into two main groups, called serial and parallel HEVs, according to the way their energy converters are linked together. This study deals mainly with parallel HEVs (Fig. 1).

In this arrangement, both motors are mechanically linked to the wheels, so their speed depends on the vehicle speed. In comparison with the serial arrangement, a parallel HEV provides a shorter energy chain, which ensures a high efficiency and a low production cost. The main drawback is the complexity of the powertrain mechanical transmission.

The present work is related to parallel torque addition HEVs only. The control strategy has to determine the torque of both motors and the gear using the wheel torque set point given by the driver and the battery SOC.

The relation between the different torques is

$$T_{\mathrm{w}} = R(k_{\mathrm{r}})(T_{\mathrm{e}} + \rho T_{\mathrm{m}}) \tag{1}$$

The various efficiencies are not taken into account in the

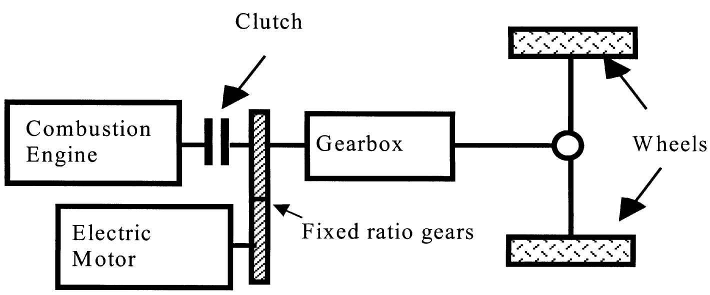

Fig. 1 General single-shaft parallel hybrid powertrain

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formulae. The speed of the vehicle is given by

$$n_{\mathrm{w}} = \frac{n_{\mathrm{e}}}{R(k_{\mathrm{r}})} = \frac{n_{\mathrm{m}}}{\rho R(k_{\mathrm{r}})} \tag{2}$$

Of course, torques and speeds are limited by the following mechanical constraints:

$$0 < T_{\mathrm{e}} < T_{\mathrm{e\_max}}(n_{\mathrm{e}}) \qquad \text{with } 0 < n_{\mathrm{e}} < n_{\mathrm{e\_max}}$$

$$T_{\mathrm{m\_min}}(n_{\mathrm{m}}) < T_{\mathrm{m}} < T_{\mathrm{m\_max}}(n_{\mathrm{m}})$$

$$\text{with } 0 < n_{\mathrm{m}} < n_{\mathrm{e\_max}}\rho$$

The wheel torque is the sum of the engine and the electric motor torques. In this case the main problem is that an optimal distribution for these two torques is unknown. In other words, the power control of the powertrain needs to be defined in order to use the electrical energy in the best way.

A model integrating all the components of the powertrain was built [**3**]. Good adaptability of the model is required to analyse and compare the various configurations and technologies. The modelling is thus based on a modular approach allowing the separate definition of each part of the powertrain, which can then be easily connected to create several configurations. The different components of a powertrain (motor, engine, gearbox, clutch, battery, body, etc.) are gathered in a database. Modelling and simulations were carried out with MATLAB and SIMULINK. Figure 2 shows a block diagram of the complete powertrain studied in this paper.

The simulations are computed using normalized speed cycles. Since the model is mainly devoted to energy management concerns, small time constants have been neglected.

A real-time interface allows the model to be used either in simulation or in real-time control for the prototype. In the latter case, the set point provided to the control strategy is no longer derived from the speed cycle but is directly given by the driver through the gas pedal.

The control strategy block in the model has not yet been discussed. That is the main focus of this paper and it can be presented as an optimization problem.

3 CONTROL STRATEGY

3.1 General presentation as an optimization problem

The driver continuously gives a total torque set point at the level of the wheels. Let c be a cycle and $i \in \{1, \ldots, N\}$ a sample. Clearly, equations (1) and (2) show that only one torque (the electrical torque T_{m} has been chosen in this paper) and the gear k_{r} need to be optimized. The

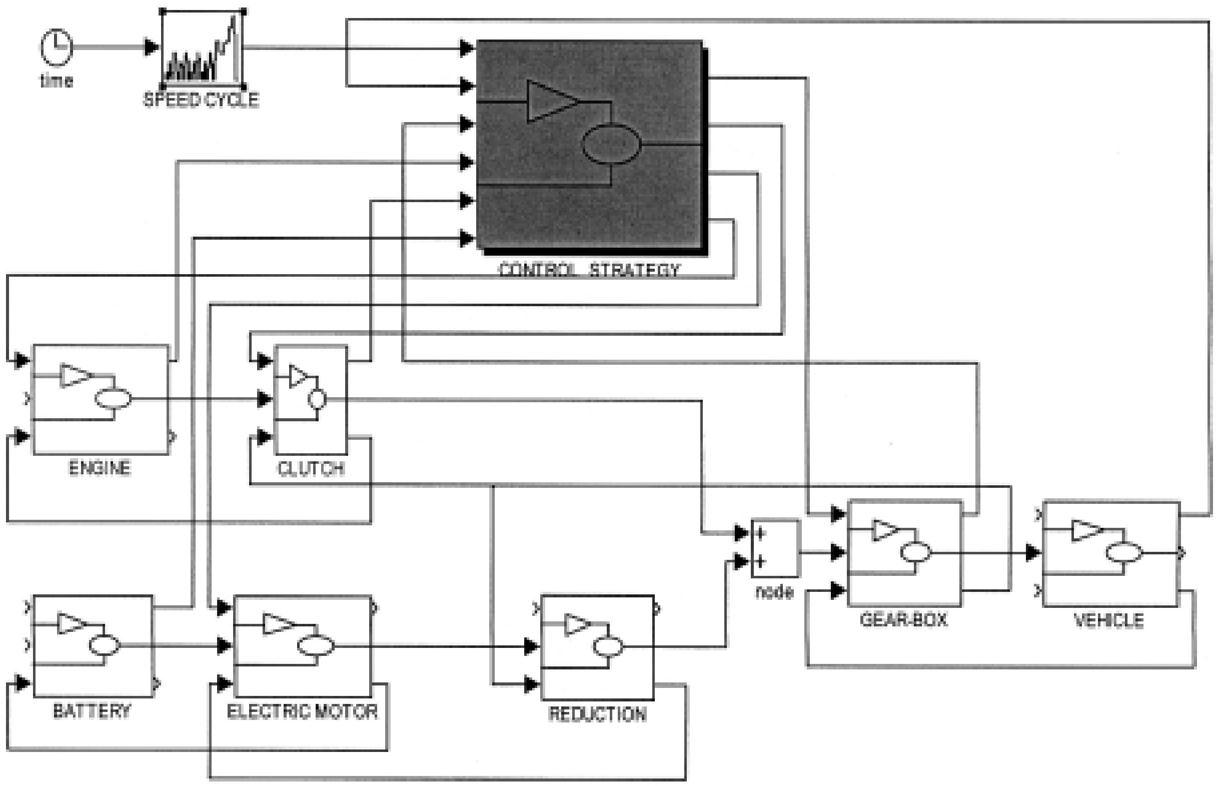

Fig. 2 SIMULINK model of a parallel hybrid powertrain

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problem is thus

1. Find the gear k_r in a limited set of solutions defined by the gearbox design.
2. Find the electric motor torque T_m, which can be positive or negative.

A solution is obtained by tuning $T_m(i)$ and $k_r(i)$ under the mechanical constraints given above in order to minimize the engine fuel consumption on the defined driving run:

$$\min_{\{T_m(i),\, k_r(i),\, i \in \{1,\ldots,N\}\}} \sum_{i=1}^{N} F_e(i) \tag{3}$$

However, several solutions to this problem exist depending on the varying final state of charge of the battery. Therefore, this final state of charge is set and the fuel consumption is used to compare different solutions. In order to compare different solutions, a natural way is to set an *a priori* amount of battery energy allowed and to compare the fuel consumption of the solutions. This new constraint on the battery state of charge is

$$\sum_{i=1}^{N} P_{batt}(i)\Delta = E \tag{4}$$

The battery power $P_{batt}(i)$ is assessed by taking the efficiency of the whole electric powertrain (motor, power unit, battery) into account.

The overall optimization problem is a complex one and will be discussed later in the paper. The main problem of this approach is that the whole driving schedule has to be known *a priori*, and thus real-time control will not be straightforward. A way to avoid this drawback is to replace the global criterion by a local one, reducing the problem to a minimization of fuel consumption at each instant:

$$\min_{\{T_m(i),\, k_r(i),\, i \in \{1,\ldots,N\}\}} \sum_{i=1}^{N} F_e(i)$$

becomes

$$\sum_{i=1}^{N} \min_{\{T_m(i),\, k_r(i),\, i \in \{1,\ldots,N\}\}} F_e(i) \tag{5}$$

Clearly, these two criteria are not equivalent. Indeed the first, equation (3), through a non-linear optimization algorithm, can give a global optimal solution (see Section 3.4) which is not directly available for real-time control. In contrast, the second, equation (5), gives a local optimal solution which can be easily used for real-time control.

These two approaches are studied in the next sections. Firstly, a control strategy based on an instantaneous optimization, equation (5), is proposed. Secondly, in order to validate this 'local' approach, an optimization based on the global criterion and the well-known simulated annealing method is carried out.

The two next sections present two local optimizations that will be compared later. The first one is proposed by Seiler and Schröder from Daimler-Benz AG [**1**] and is based on minimization of losses. The second one proposes that an equivalent fuel flow consumption for the electric motor should be taken into account [**8**].

3.2 Loss minimization strategy (LMS) [1]

This strategy is based on the minimization of efficiency loss for the entire powertrain. It is assumed that no efficiency loss occurs at the operating point at which there is a minimum specific fuel consumption. At any moment, the powertrain operating point for a particular driving condition is chosen so that the total efficiency loss is minimized. By minimizing the losses, the operating point of the powertrain is entirely defined by the driving condition. Then, the total loss on a run can be written

$$\sum_{i=1}^{N} \min_{\{T_m(i),\, k_r(i),\, i \in \{1,\ldots,N\}\}} P_l(i) \tag{6}$$

The principle is to keep the SOC of the battery close to a set point. Since the operating point determined from the loss minimization cannot fulfil this constraint, it is adjusted with a sensitivity analysis. This sensitivity is defined by $\Delta P_l(i)/\Delta I_{batt}(i)$. The whole approach requires the assessment of a new operating point with respect to a sensitivity constraint on the SOC written as

$$\max_{\{T_m(i),\, k_r(i)\}} |\Delta I_{batt}(t)|$$

$$\text{under the constraint } S(i) = \frac{\Delta P_l(i)}{\Delta I_{batt}(i)}$$

In other words, the solution is chosen among all the acceptable operating points in order to correct the battery SOC in the quickest possible way, corresponding to the highest current variation.

The idea of this strategy is to keep the SOC of the battery close to a set value. However, since the strategy tries to use the battery on a constant SOC during a long run, each charge of the battery has to be followed by a discharge and vice versa. So, more losses should be taken into account. This kind of forecasting is included in the strategy presented in the following section.

3.3 Equivalent consumption minimization strategy (ECMS) [8]

Clearly, for a long run, the difference between final and

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initial state of charge of the battery is neglected in comparison with fuel consumption:

$$\sum_{i=1}^{N} P_{\mathrm{batt}}(i)\Delta \approx 0 \tag{7}$$

In this case, the battery is only used as an energy buffer. Since the energy is fuel, the idea is to consider the battery as an auxiliary reversible fuel tank. A particular operating point of the powertrain leads to two cases:

(a) the battery current is positive (discharge case)—a recharge with the ICE will require some additional fuel consumption;
(b) the battery current is negative (charge case)—the stored electrical energy will be used to alleviate ICE load for running the car, which implies a fuel saving.

In both cases, an equivalent fuel flow can be associated with any operating point of the electric motor. This equivalent fuel flow of the electric motor is obtained using the route from fuel to electrical energy. This route is depicted in Fig. 3 for a positive battery current and Fig. 4 for a negative one:

1. In the discharge case, the electric motor provides mechanical power. The dotted route is related to the future return of the used instantaneous electrical energy. Of course, the operating point of this recharge cannot be known *a priori*, and thus an approximate mean efficiency has been set.
2. In the charge case, the electric motor receives mechanical energy and converts it into electrical energy stored in the battery (Fig. 4). The dotted route is related to the future use of this electrical energy to produce mechanical power. This amount of mechanical energy will not have to be produced by the ICE and is considered as a fuel saving. In this case the equivalent fuel flow of the electric motor is negative.

A map of equivalent fuel flow for the electric motor is then obtained. The powertrain operating point is selected

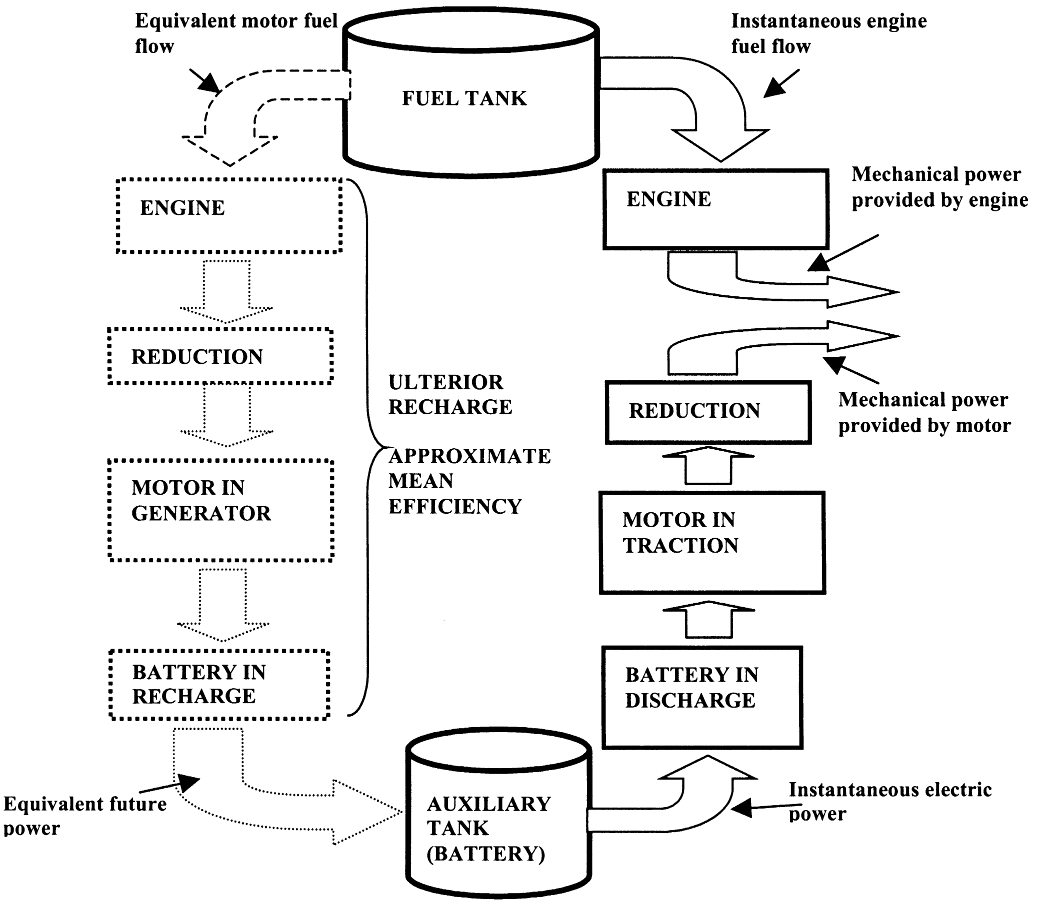

Fig. 3 Energy route for the equivalent fuel flow consumption of the electric motor for a positive current (discharge case)

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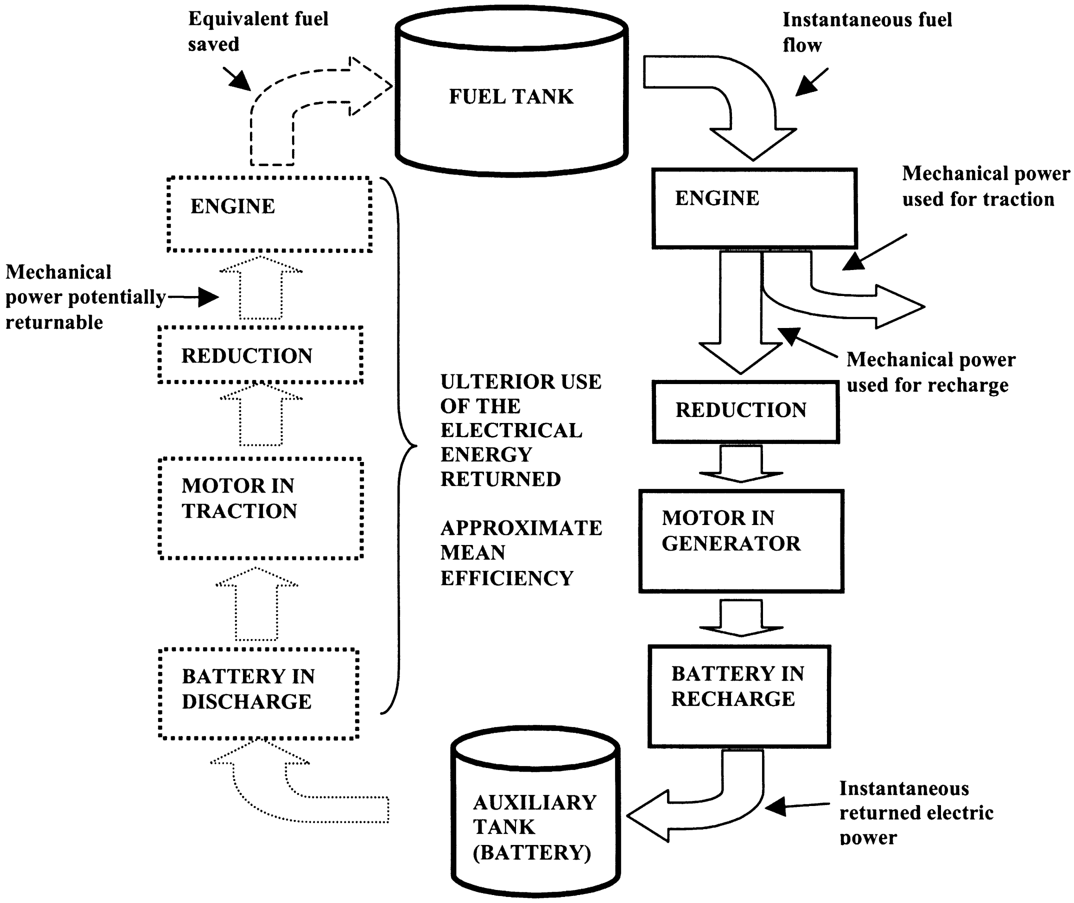

Fig. 4 Energy route for the equivalent fuel flow consumption of the electric motor for a negative current (charge case)

to minimize the sum of the engine fuel flow and the equivalent fuel flow of the electric motor. The total equivalent fuel flow for a run is written as

$$\sum_{i=1}^{N} \min_{\{T_m(i),\, k_r(i),\, i\in\{1,\ldots,N\}\}} [F_e(i) + F_m(i)]$$

Two optimal maps, one for the torque motor T_m and the second for the gear number k_r are also obtained. They are functions of speed and torque to the wheels.

Each operating point of the powertrain defines a battery current. Of course, on a long drive, the battery SOC will not remain at its nominal value. The goal is to keep, according to the driving condition, the SOC within minimum and maximum thresholds that ensure good operation of the battery. As for LMS strategy the battery current is increased or decreased according to a sensitivity analysis. Let this shift cost or sensitivity be defined by $\Delta F(i)/\Delta I_{batt}(i)$. The whole approach requires the assessment of a new operating point with respect to a sensitivity constraint on the state of charge written as

$$\max_{\{T_m(i),\, k_r(i)\}} |\Delta I_{batt}(t)|$$

under the constraint $S(i) = \dfrac{\Delta F(i)}{\Delta I_{batt}(i)}$

The higher the shift cost is, the more the mean battery current can be moved away from the optimal one while being in the supplementary equivalent fuel flow bounds.

Finally, the powertrain is controlled according to the maps of the motor torque T_m and the number of gears k_r. The operating point is then shifted in order to move toward the SOC target with respect to the shift cost. The shift cost is calculated by a PI controller using the error between the current SOC and the target value. Three cases may occur:

(a) the SOC is on the target value—the shift cost is null and the optimal operating points of the powertrain are kept;

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(b) the SOC is too high—the shift cost is positive and the operating points are moved in order to increase the mean battery current;
(c) the SOC is too low—the shift cost is negative and the operating points are moved in order to decrease the mean battery current.

As said previously, the problem can be seen as a global optimization problem and can be solved with an optimization technique. Recall that a global optimization cannot be used for real-time control since it is necessary to know *a priori* the driving schedule. Nevertheless, it is a good off-line tool to evaluate how far the results of the two instantaneous strategies are from an optimal solution.

3.4 Global optimization based on simulated annealing

The lack of analytical models (engine, battery, . . .) leads us to choose a heuristic method. As numerous local minima can rise to globally similar performances, simple gradient techniques are to be avoided. In the present case, the simulated annealing method **[9]** was chosen according to several criteria:

(a) resources required;
(b) algorithm complexity;
(c) CPU time versus problem size.

To outperform this method, simulated annealing with heating cycles proposed by Bonnemoy and Hamma **[10]** is used. The optimization problem can be written as

$$\min_{X(k)\in\aleph} \sum_{i=1}^{N} F_e(i)$$

under the constraints

$$\sum_{i=1}^{N} P_{\mathrm{batt}}(i)\Delta = E$$

$$0 < T_e(i) < T_{e\_max}[n_e(i)] \qquad \forall i \in \{1, \dots, N\}$$

$$T_{m\_min}[n_m(i)] < T_m(i) < T_{m\_max}[n_m(i)] \qquad \forall i \in \{1, \dots, N\}$$

$$0 < n_m(i) < n_{e\_max}\rho \qquad \forall i \in \{1, \dots, N\}$$

$$0 < n_e(i) < n_{e\_max} \qquad \forall i \in \{1, \dots, N\}$$

where $\aleph \subset n_{\mathrm{gears}} \times \Re^n$ is the set of solutions and

$$X = \begin{bmatrix} T_m(1) & k_r(1) \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ T_m(N) & k_r(N) \end{bmatrix} \in \aleph$$

Because of the lack of an engine model, F_e, T_{e_max}, T_{m_min} and T_{m_max} are given by maps. According to the Metropolis algorithm, a new solution $X(k+1)$ is chosen in the neighbourhood of $X(k)$. To avoid the use of different types of variables for $X(k)$ (i.e. integer and real), and to reduce the research space, a new set of solution $\aleph 1 \subset \Re^n$ is defined and

$$X(k) = \begin{bmatrix} T_m(k,1)R[k_r(k,1)] \\ \cdot \\ \cdot \\ \cdot \\ T_m(k,N)R[k_r(k,N)] \end{bmatrix} \in \aleph 1, \quad \text{the } k\text{th solution}$$

where the product $T_m(k,i)R[k_r(k,i)]$ represents the part of the wheel torque provided by the electric motor at the sample time i. To obtain a new solution $X(k+1)$ a draw is done in the neighbourhood of $X(k)$ with respect to the inequality constraints: $X(k+1) = X(k) + \Delta(k)$. Of course the equality constraint

$$\sum_{i=1}^{N} P_{\mathrm{batt}}(i)\Delta = E$$

is generally not satisfied, i.e. $X(k+1) \notin \aleph 1$. A simple way to ensure that $X(k+1) \in \aleph 1$ is to apply an iterative algorithm based on the approximate relation $P_{\mathrm{batt}}(k+1,i) \approx T_m(k+1,i)n_m(k+1,i)$.

A Boltzmann probability for the acceptance law is used: $H[X(k+1)] = e^{\delta/T}$ where $H[X(k+1)]$ is the acceptance probability of $X(k+1)$, δ the variation of the cost function and T the temperature. The temperature follows an exponential schedule with the heating cycle **[10]**.

To start the algorithm, an initial solution $X(0)$ in the set of admissible solutions $\aleph 1$ must be available. It can be supplied by

(a) an existing control strategy applied to the run (LMS or ECMS, for example) or
(b) generating a random solution.

4 SIMULATION RESULTS

4.1 Context of the simulations

To illustrate the results of these different approaches,

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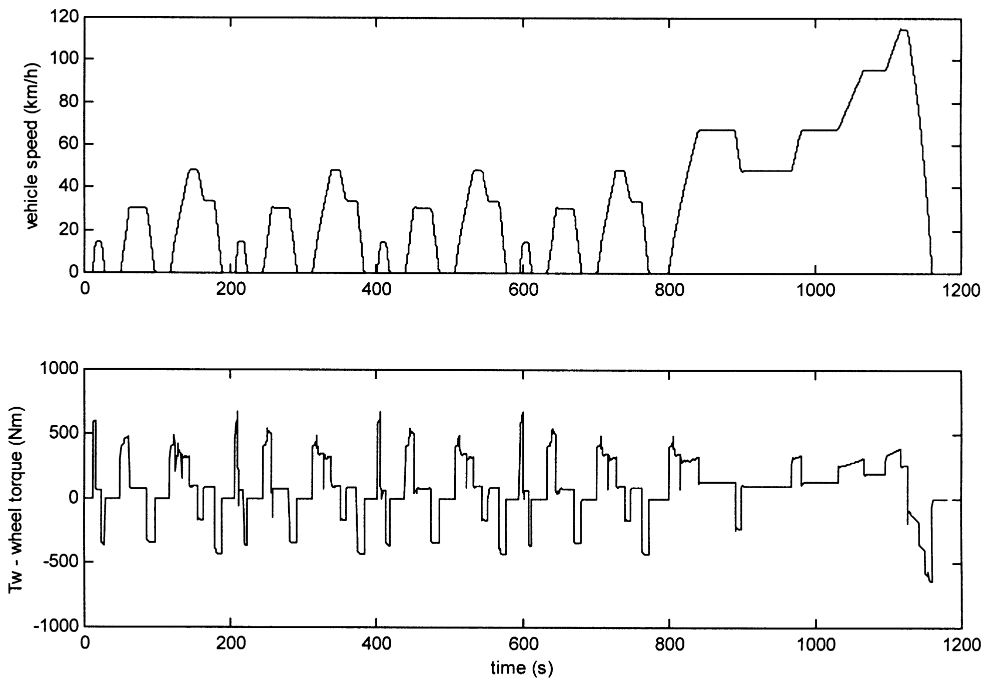

Fig. 5 Speed CEN and corresponding wheel torque required

some simulations have been carried out with a single-shaft parallel hybrid vehicle with a two-gear gearbox. The model is based on an existing prototype of total mass 1608 kg, and the European normalized cycle (CEN) has been chosen (duration: 1180 s). The features of the car define the wheel torque required to ensure the speed cycle (Fig. 5).

With a hybrid powertrain, the on–off management of the engine clearly influences the total fuel consumption. Of course a lower consumption can be obtained if the engine is turned off as soon as it is no longer prompted. It should be noted that, in this case, the number of on–off states will not be realistic. Therefore, in these simulations, the engine is turned on as soon as it is prompted and is only turned off when the car has been stopped for 3 s.

According to the equality constraint in equation (4), the different fuel consumptions can only be compared if the total electrical energy consumption is null (final state of charge = initial state of charge):

$$\sum_{i=1}^{N} P_{\text{batt}}(i)\Delta = 0$$

To have a basis of comparison, the first trial was done with the standard vehicle weighing 300 kg less (the battery and the electric motor weights). The fuel consumption with the same ICE used in the hybrid powertrain prototype is about 8.0 l/100 km for this cycle.

4.2 Loss minimization strategy (LMS)

The powertrain utilization during the cycle is presented in Fig. 6. In the various presented figures, the curves represent:

(a) ICE torque (N m),
(b) motor torque (N m),
(c) gear number,
(d) SOC of the battery (per cent) and
(e) sensitivity (W/A)

While the SOC is decreasing, the sensitivity leaves the zero level in order to allow the recharge of the battery. The fuel consumption with the loss minimization strategy is equal to 563 g, representing 7.01 l/100 km.

4.3 Equivalent fuel consumption minimization strategy (ECMS)

The equivalent fuel flow has been calculated for the electric motor according to the estimated mean efficiency for the prototype powertrain [**3**, **11**]. For this special case the optimal operating point of the powertrain is summarized in Figs 7 (the optimal gear number) and 8 (the optimal engine torque).

With the same parameters used for the LMS, a simulation is computed according to the instantaneous

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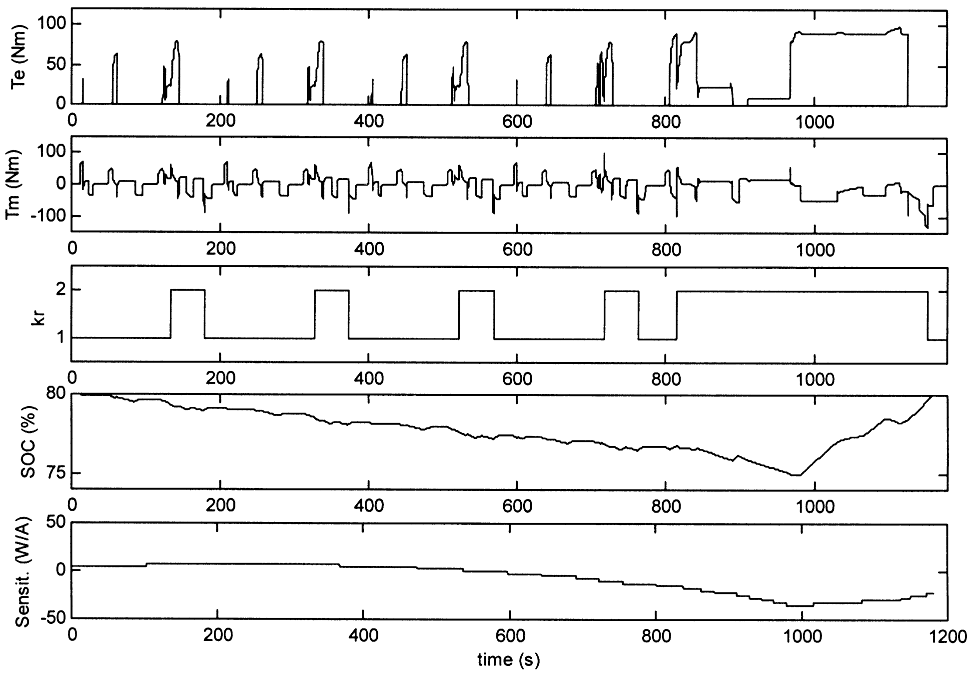

Fig. 6 Results with instantaneous loss minimization

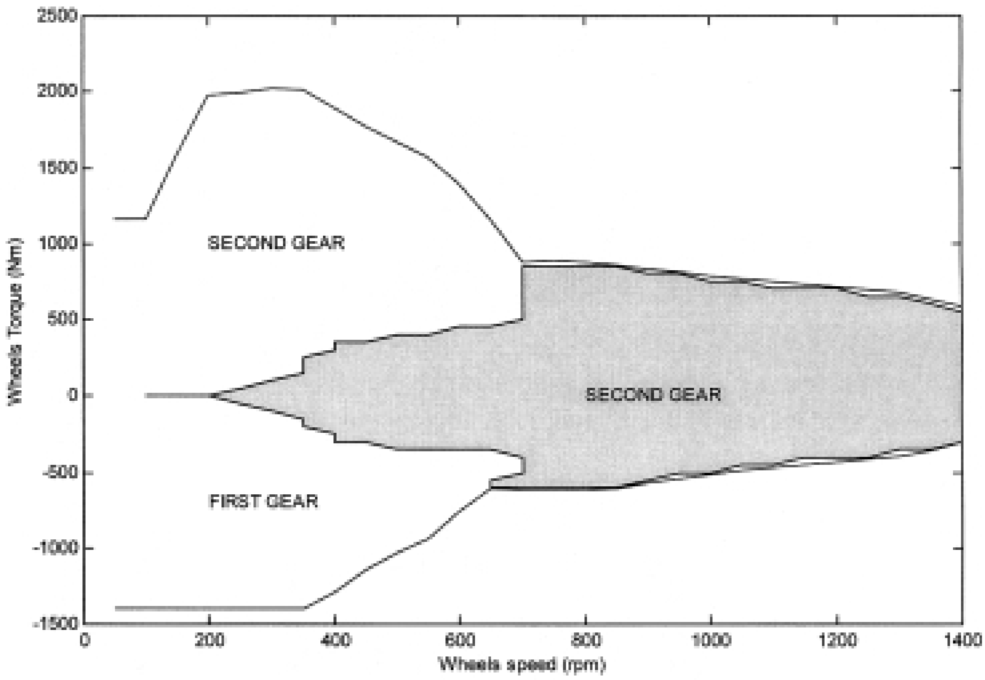

Fig. 7 Optimal gear number

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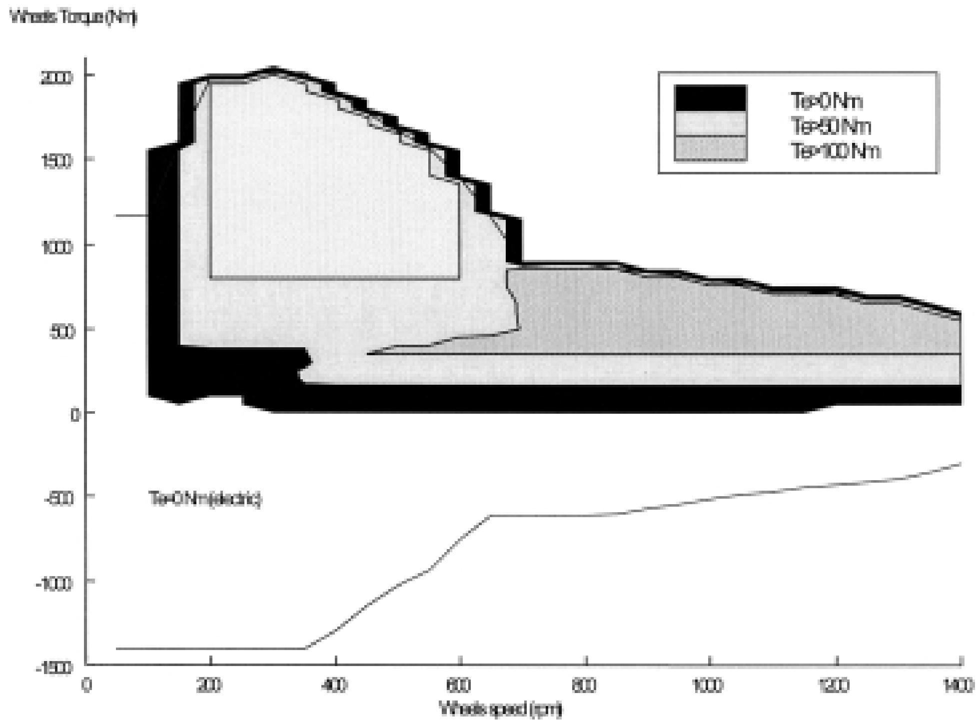

Fig. 8 Optimal engine torque

equivalent consumption minimization strategy. Results are shown in Fig. 9.

The lower the shift cost is, the more the engine is prompted (T_e curve), in order to foster the charge of the battery and vice versa. This is clearly seen during the four microcycles (i.e. the first 800 s of the CEN) in Fig. 5: the engine use is increased while the shift cost is decreased. The fuel consumption for this run is 532 g, representing 6.6 l/100 km.

4.4 Global optimization with simulated annealing

Since the driving schedule is known, the preceding results

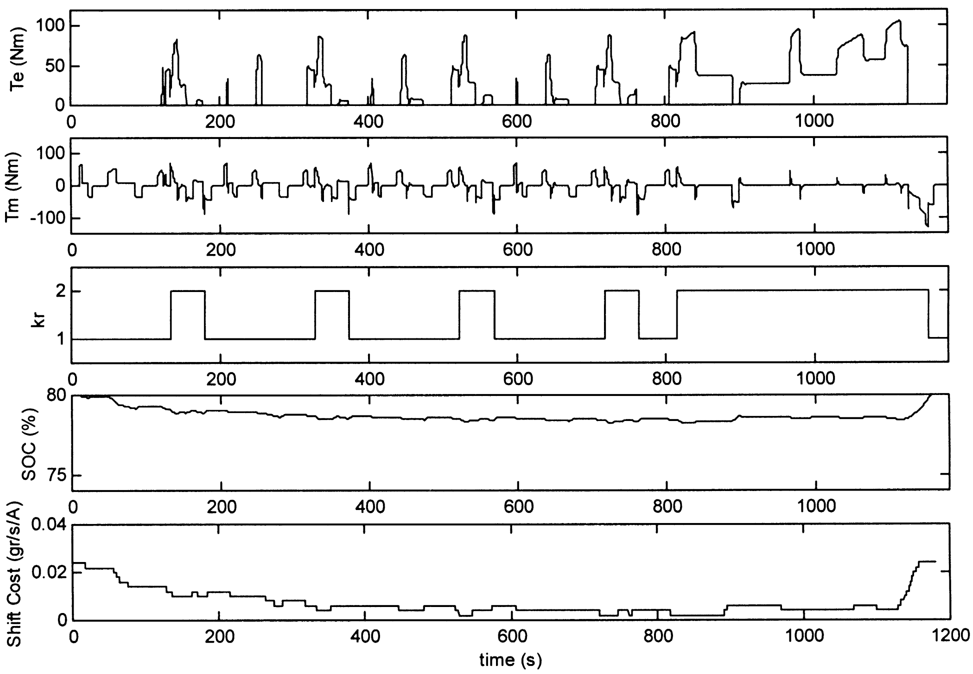

Fig. 9 Results with instantaneous fuel flow minimization

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can be compared with an optimal solution provided by the simulated annealing method. An initial solution for the optimization algorithm can be a random one or a solution obtained with the previous instantaneous optimizations.

4.4.1 From a random solution

A random initial solution $X(0)$ is generated and the total fuel consumption in the CEN is

$$\sum_{i=1}^{N} F_e(i) = 562.72 \text{ g}$$

Simulated annealing parameters are set as follows: temperature schedule is exponential with heating cycle, its initial value is 0.15 and the final temperature is 0.001. A temperature plateau is ended as soon as one of the following stopping criteria is satisfied: the number of iterations since the last decrease of the cost function exceeds 7000 or the number of iterations since the last optimal fuel consumption improvement exceeds 10 000. The acceptance probability is $e^{-\Delta/T}$, where Δ is the cost function variation during the two last iterations. To provide fine tuning for the optimal solution during low temperature plateaux, the maximal torque disturbance allowable decreases according to an exponential law.

After 300 000 iterations, the total fuel consumption is

$$\sum_{i=1}^{N} F_e(i) = 513.39 \text{ g}$$

corresponding to 6.37 l/100 km. This solution is drawn in Fig. 10.

4.4.2 From a fuel consumption minimization solution

$X(0)$ comes from the ECMS strategy (Fig. 9). After 300 000 iterations the total fuel consumption is

$$\sum_{i=1}^{N} F_e(i) = 504.16 \text{ g}$$

corresponding to 6.25 l/100 km. Figure 11 shows the evolution of total fuel consumption, and the solution is drawn in Fig. 12.

The final power distribution is different from the others. Nevertheless, it may be noticed that the gear distribution obtained in Fig. 12 is not realistic.

5 DISCUSSION AND CONCLUSION

Table 1 sums up the various fuel consumptions obtained with the different strategies.

First it should be noted that, for the same vehicle considered in simulations with an ICE and a five-gear gearbox, the fuel consumption is about 8.0 l/100 km. The improvement for the two instantaneous strategies, LMS and ECMS, in spite of an excess load of about 300 kg over the same car with an ICE and a gearbox with only two gears, is really significant.

For the instantaneous strategies, the main advantage of the ECMS strategy over the LMS strategy is that it takes into account the energy cost for regenerating

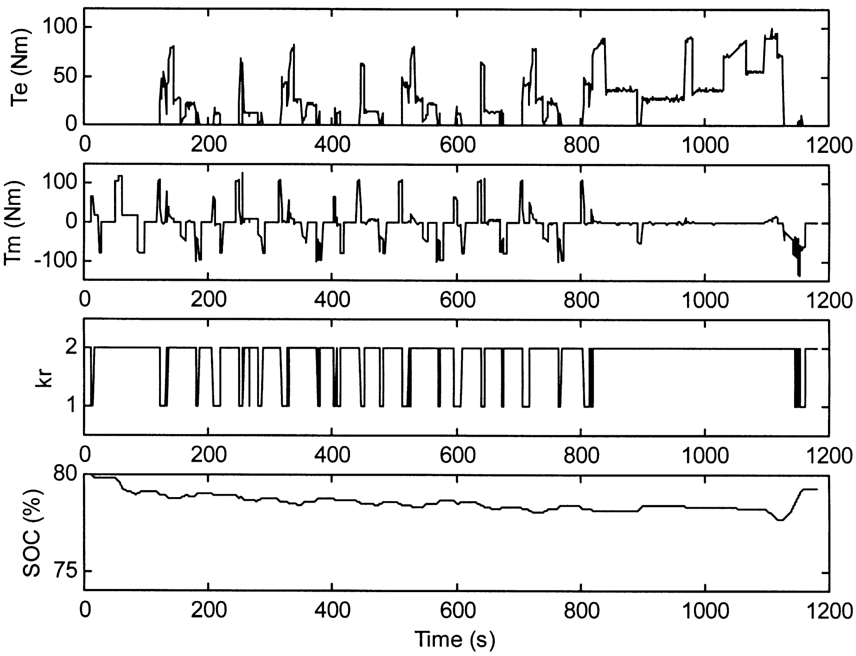

Fig. 10 Results of optimization from a random solution

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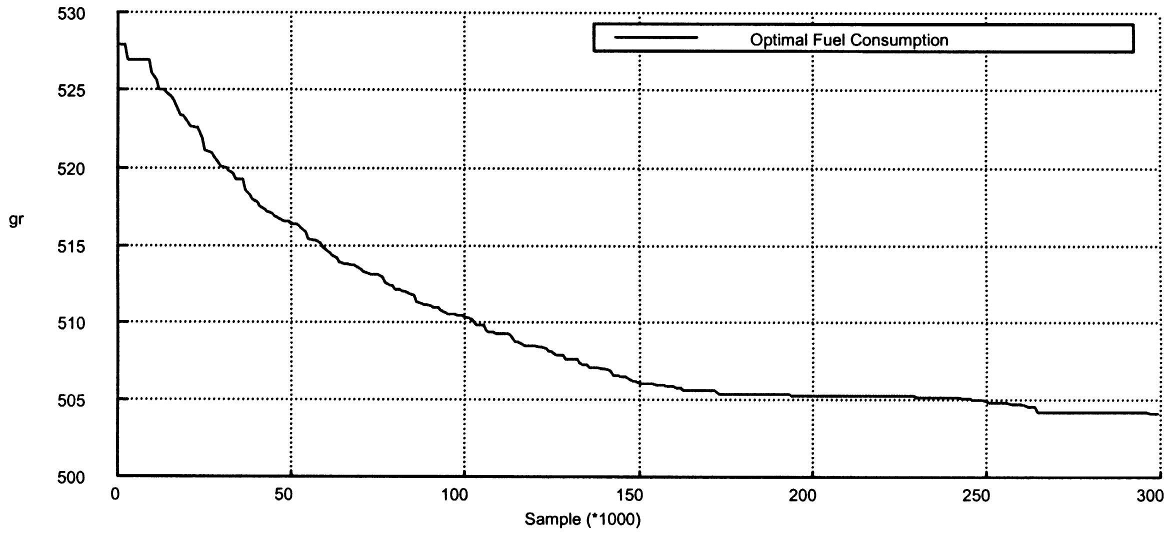

Fig. 11 Evolution of total fuel consumption starting from the ECMS solution

the SOC of the battery. The results show that this advantage allows an improvement of fuel consumption of more than 5 per cent over the LMS strategy. Another important remark is that this improvement is achieved without increasing the difficulty for real-time control implementation.

For the global optimization with simulated annealing, the improvement of the fuel consumption is about 4 per cent in the best case over ECMS. Recall that this optimization was done only to assess the instantaneous strategies and, since it is an off-line optimization, the results obtained cannot be used for real-time control. Moreover, the improvement seems to be obtained to the detriment of a realistic solution according to the distribution of operating points. It shows that the solution obtained with ECMS is not very far from the optimal distribution. It is interesting to note that the instantaneous fuel consumption minimization is not very far from the optimal management of the powertrain in terms of fuel consumption.

Clearly the CEN is too basic for general conclusions to be extracted. Nevertheless, it is a good way to evaluate solutions in simulation before real-time control implementation.

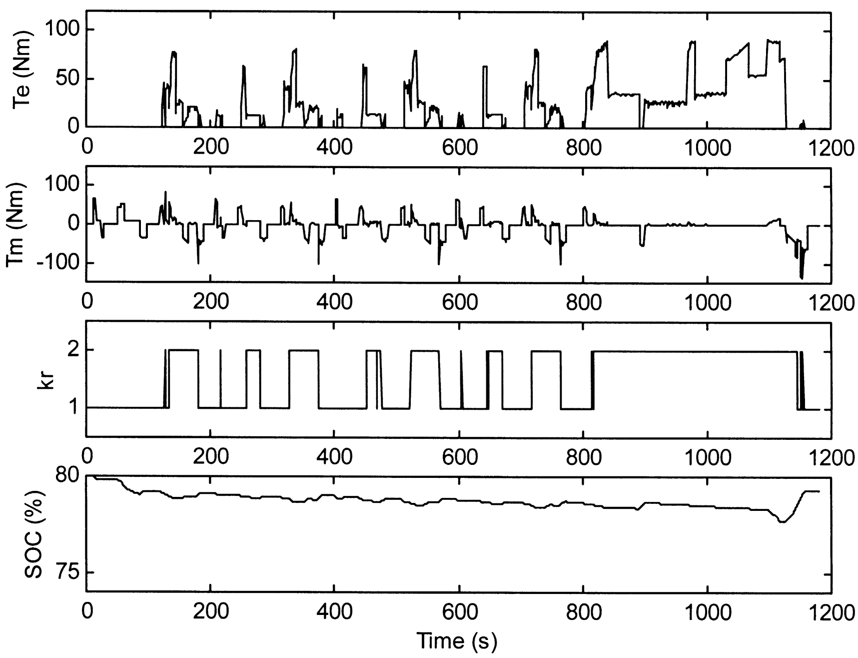

Fig. 12 Results of optimization from the ECMS solution

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Table 1 Fuel consumption comparison on CEN cycle with the prototype

	ICE (total mass of the car, 1308 kg; five-gear gearbox)	Hybrid powertrain (total mass of the car, 1608 kg; two-gear gearbox)			
				Off-line global optimization with simulated annealing	
		LMS [1]	ECMS	$X(0)$ = random solution	$X(0)$ = ECMS solution
Fuel consumption	8.0 l/100 km	7.01 l/100 km	6.6 l/100 km	6.37 l/100 km	6.25 l/100 km
Fuel save over ICE		12%	17.5%	20.5%	22%

Finally, it should be noted that the proposed strategy can be applied to any kind of parallel HEV powertrain and any kind of gearbox.

The objective of this study was to find a real-time power control strategy for a hybrid powertrain. An approach based on an instantaneous equivalent fuel consumption minimization was favoured. This solution also allows the SOC of the battery to be kept in acceptable defined bounds.

In order to justify the approach this solution was compared with other methods, firstly on the basis of a similar idea but involving loss minimization [**1**] and secondly on the basis of a global optimization. The present solution appears to be better for the special case presented in this paper. It has been implemented in a prototype and satisfactory operation has been obtained. Some trials on road circuits should confirm the expected saving fuel consumption.

The next step is to improve the on–off management of the ICE, which it is assumed will seriously lower the global fuel consumption.

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