Energetic Optimization of the Driving Speed based on Geographic Information System Data

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***Abstract*—This work is based on the road-trip knowledge in order to reduce the energy consumption of a vehicle. The proposed algorithm computes the globally optimal speed profile and the associated energy consumption profile from the road-trip information. This profile is the lowest boundary of the energy required to move the vehicle. The energetic plan obtained is independent of the powertrain architecture, it can be used with any vehicle (conventional internal-combustion engine vehicle, hybrid electric vehicle and fuel cell vehicle). This optimization algorithm runs offline and (in future works) the results will be integrated into a real-time energy management system. Algorithm results are compared to experimental data obtained with a low-speed vehicle. For the same trip duration, the presented preliminary results show that the energy consumption is lower with the optimal driving cycle.**

I. Introduction

Several recent studies have reported that the transportation sector is a significant greenhouse gas emission source [1]. Various approaches based mainly on the electrification of the vehicle powertrain have been proposed in order to reduce these pollutants: hybrid electric powertrain, plug-in hybrid electric powertrain and all range plug-in electric powertrain [2]. Moreover, the hydrogen technologies (based on a fuel cell system or on a combustion engine) seems to be a promising solution for the zero emission vehicle [3], [4].

Nevertheless, in this paper, we propose an independent of the powertrain solution to evaluate an energy efficient consumption profile of the vehicle for trip planning. The amount of mechanical energy required to move the vehicle must be less than the energy stored on the vehicle in order to complete the trip without refuelling. The refuelling problem is particularly important for the emerging all electric vehicle technologies for which there is no wide deployment of battery recharging infrastructures [5]. So, the need for a method that can provide an efficient energy consumption profile estimation is required to properly plan the energy usage.

Some commonly found methods in literature make use of previously store driving cycles for a given trip in order to compute the required energy consumption. However, this approach is sensitive to the human driver behaviour during the trip, as well as the traffic conditions which may be difficult to be predicted [6], [7], [8].

In a near future, the wide deployment of automotive telemetric infrastructures will make it realistically easy to collect some driving condition data such as the route segment speed limits and the position of the traffic light [9]. The proposed solution in this paper takes advantage on this data extracted from a Geographic Information System (GIS). Given the GIS data, an energy efficient driving cycle is computed offline by solving a non linear optimization problem and by using only the vehicle physical properties. This driving cycle is further used to derive an energy efficient profile and thereafter, to compute the total mechanical energy required, to complete the trip.

The main objective of this work is to show that for the same route and for the same trip duration, the energy consumption obtained with the proposed method is less than the energy used by the vehicle when driven by a human. Furthermore, this efficient mechanical energy consumption profile can be used as a reference guide for a human driver in order to save energy. Moreover, into a more complex powertrain like hybrid electric or fuel cell vehicles, the results can be used for the real time energy management and the power splitting between the different energy sources.

The rest of the paper is organized as follows. The vehicle energetic model, the efficient energy consumption profile and the preliminary experimental results are discussed in sections II, III and IV, respectively. The conclusion is presented in section V.

II. Vehicle Model for Energy Management

The presented work is independent of the powertrain architecture and consequently, the model used for the optimization algorithm takes into account only the vehicle dynamic and the resistive force. The longitudinal motion of the vehicle is represented by equation (1) and the corresponding mechanical power is represented by equation (2).

$$\begin{aligned} F_v &= M_v\dot{v} + \frac{1}{2}\rho_a C_d A_v v_d^2 \\ &\quad + M_v g sin(\theta) + M_v g \mu cos(\theta) \end{aligned} \qquad (1)$$

where M_v, g, ρ_a, μ, C_d and A_v represent respectively the vehicle's total mass, the gravity constant, the air density, the

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rolling resistance coefficient, the air drag coefficient and the active frontal area. These parameters are known for a given vehicle and a given rolling condition. θ, $\dot{v}$ and v_d represent respectively the road grade, the longitudinal acceleration and the vehicle speed relative to the air.

$$P_m = F_v v \tag{2}$$

III. Energy Consumption Planning

The objective of the planning is to provide a time series of the mechanical energy used to move the vehicle over a given route by considering only the prescribed speed limit, the road grade and the position of traffic lights and stop signs on each route segment. These road informations are commonly available for each urban road and highway segment, and are independent of the vehicle driver's behavior as well as the traffic condition. The time series of the speed limit (speed limit profile) for all road-trip segments may have abrupt changes in the speed values. In practice, such sharp changes of speed values produce high accelerations or decelerations as the vehicle tries to follow the speed limit profile. The presence of high accelerations is definitively not energetically efficient. To derive the most energy-efficient speed profile for a typical vehicle whilst respecting the trip duration, we considered three main constraints: the speed limits and the road grade of each segment, and the travel time between two consecutive stops. The energy-efficient speed profile will be used to derive an optimal mechanical energy consumption profile.

A. Problem Formulation for Efficient Energy Planning

1) Vehicle State Model and Cost Function Definition : In order to find the best possible energy-efficient driving cycle, assume that a virtual vehicle (by opposition to the vehicle under study) is following exactly the speed limit profile represented by the sequence $\{v^v(i), i = 0, 1, 2, ..., N_p\}$, where i and N_p represent the timestamp and the number of samples, respectively. Actually, if there is no traffic perturbation, this speed profile is the worst speed profile from an energetic point of view, as it implies large accelerations and decelerations at the speed limit boundaries. The virtual vehicle state is represented by $X^v(i) = [x^v(i), v^v(i)]^T$ where $x^v(i)$ is its longitudinal position and where $v^v(i)$ is its longitudinal velocity relatively to the ground. On the other hands, the state of the vehicle under study is represented by $X(i) = [x(i), v(i)]^T$ where $x(i)$ and $v(i)$ represent respectively the real vehicle longitudinal position and its longitudinal velocity relatively to the ground. This vehicle is, of course, subject to physical limitations such as acceleration/deceleration bounds.

The idea is to formulate an optimal trajectory tracking problem between the vehicle under study (the real vehicle with physical limitations) and the virtual vehicle (with no physical limitations) by minimizing the following cost function:

$$J(0) = J(N_p) + \sum_{i=0}^{N_p-1} \{J(i)\} \tag{3}$$

where:

$$J(N_p) = \frac{1}{2}\left[X(N_p) - X^v(N_p)\right]^T Q(N_p)\left[X(N_p) - X^v(N_p)\right] \tag{4}$$

and where:

$$\begin{aligned} J(i) \;=\; & \left[X(i) - X^v(i)\right]^T Q(i)\left[X(i) - X^v(i)\right] \\ & + u^2(i) \end{aligned} \tag{5}$$

and where the real vehicle discrete dynamic state equation is represented by:

$$\begin{bmatrix} x(i+1) \\ v(i+1) \end{bmatrix} = \begin{bmatrix} x(i) + v(i)\Delta T \\ v(i) + u(i)\Delta T - \alpha(i)\Delta T \end{bmatrix} \tag{6}$$

where:

$$\alpha(i) = \frac{1}{2M_v}\rho_a A_v C_d v^2(i) + g sin\left(\theta\right) + \mu g cos\left(\theta\right) \tag{7}$$

and where $u(i)$ is the command which represents the mechanical force applied by the electric propulsion system divided by the vehicle total mass and where ΔT is the sampling period. N_p will be the number of samples.

$x^v(i+1) = x^v(i) + v^v(i)\Delta T$ is the trajectory obtained when the virtual vehicle is moving on the trip route at the speed limits v^v. $Q \geq 0$ represents the penalty matrix associated with the deviation between X^v and X. The first term of the cost function (5) will let X (trajectory x and driving cycle v) be close to X^v over the trip route, whereas the second term is introduced to take into account the requirement of low command on the real vehicle when tracking the virtual vehicle through the speed limits.

2) Optimal State Tracking: The optimal command sequence $\{u^*(i), i = 0, 1, 2, ..., N_p - 1\}$ is defined as:

$$u^* = \arg\min_u J(0) \tag{8}$$

with the following nonlinear constraints:

$$u_{min} \leq u(i) \leq u_{max} \tag{9}$$

$$v_{min} \leq v(i) \leq v_{max} \tag{10}$$

where u_{min}, u_{max}, v_{min} and v_{max} represent the allowed real vehicle minimum and maximum command, minimum and maximum speed, respectively.

We used the dynamic programming method to compute offline U^*. This method is one the most used for the global nonlinear optimization problems [10], [11]. The optimal sequence $\{X^*(i) = [x^*(i), v^*(i)]^T, i = 0, ..., N_p\}$ is given by:

$$\begin{bmatrix} x^*(i+1) \\ v^*(i+1) \end{bmatrix} = \begin{bmatrix} x^*(i) + v^*(i)\Delta T \\ v^*(i) + u^*(i)\Delta T - \alpha^*(i)\Delta T \end{bmatrix} \tag{11}$$

where $\alpha^*(i) = \frac{1}{2M_v}\rho_a A_v C_d (v^*(i))^2 + g sin\left(\theta\right) + \mu g cos\left(\theta\right)$.

3) Optimal Mechanical Energy Consumption Profile : The vehicle optimal driving cycle $\{v^*(i), i = 0, ..., N_p\}$ and the command sequence $\{u^*(i), i = 0, ..., N_p - 1\}$ obtained by solving the optimization problem are used to compute the optimal mechanical power profile which is represented by equation (12).

$$P_m^*(i) \quad = \quad M_v u^*(i) v^*(i) \tag{12}$$

If we assume that the vehicle starts moving from its rest position, the optimal mechanical energy profile for the trip $E_m^*(i), i > 0$ is therefore computed as follows:

$$E_m^*(i+1) = E_m^*(i) + P_m^*(i)\Delta T \tag{13}$$

The minimum mechanical energy required to move the vehicle is represented by $E^*(N_p)$. Any additional traffic perturbation will therefore increase this energy. $E^*(N_p)$ is the lower boundary value of the energy used for the whole trip. For a given route with no traffic perturbation, the energy consumption of a real vehicle with a specific powertrain architecture can be compared to $E^*(N_p)$. The difference between these two energy values is an indication of how close is the vehicle energy consumption to the minimum one.

IV. Simulation And Experimental Validations

The objective of this section is to validate global energy consumption planning algorithm and to show that for the same route and for the same trip duration, the proposed energy profile is lower than the energy profile obtained by a human driving a real electric vehicle with no traffic perturbation.

A. Presentation of the Vehicle and of the Reference Trip

The vehicle so-called Nemo is a small low-speed fuel cell hybrid electric truck (see Fig. 1) [12]. This vehicle has been modified for the research works of the Hydrogen Research Institute of UQTR (Université du Québec à Trois-Rivières). A fuel cell system and a hydrogen internal combustion engine have been integrated on the vehicle to extend its autonomy. As a result, the vehicle is being used as a test-bench for the study of different range extension technologies based on hydrogen.

Four humans drove the electric truck over the navigation route shown in Fig. 2. During the test, there was no additional traffic. Prior to drive the truck, they were asked not to exceed the prescribed maximum speed of $21km.h^{-1}$. In addition, the drivers must stop completely the vehicle at each stop sign for at least 2 seconds. Each driver is asked to complete four laps on the route. The vehicle longitudinal motion speed (driving cycle) and the time to complete the four laps were recorded and shown in Fig. 3. The four driving cycles obtained when humans were controlling the truck are quite different, even if the navigation environment was the same and the vehicle dynamics remained unchanged. In addition, the difference between the travel durations for all drivers is less than 3% of the reference travel duration of $800s$. This travel duration difference is mainly related to the average motion speed and the average stop duration imposed by each driver.

Fig. 1. Electric Truck Nemo

Fig. 2. Example of a Navigation Route with 7 Stop Signs on the Campus of Université du Québec à Trois-Rivières. The speed limit over the entire route is $21km/h$ for experimentation purposes.

TABLE I
PARAMETERS

Parameter	Value	Parameter	Value
M_v	$1200kg$	A_v	$1.2m^2$
ρ_a	$1.2kgm^{-3}$	μ	0.018
C_d	0.5	Q	$\begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$
θ	$0rad$	g	$9.81ms^{-2}$
u_{min}	$-2ms^{-2}$	u_{max}	$3.5ms^{-2}$
v_{min}	$0ms^{-1}$	v_{max}	$10ms^{-1}$
N_p	807	ΔT	$1s$

Using the recorded driving cycles and the truck physical parameters, the mechanical energy is computed. All parameters for the energy profile computation are presented in Table I.

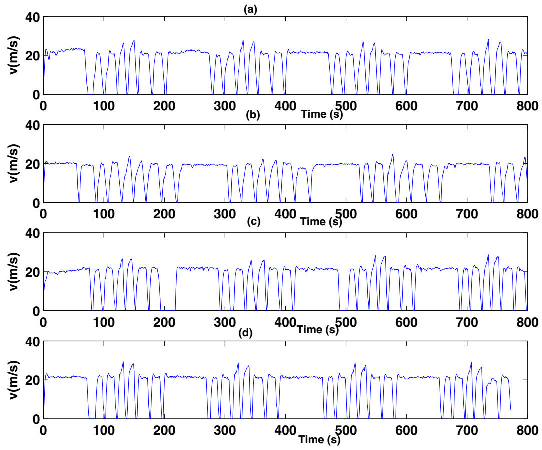

Fig. 3. Driving Cycles: (a) Driver 1; (b) Driver 2; (c) Driver 3; (d) Driver 4.

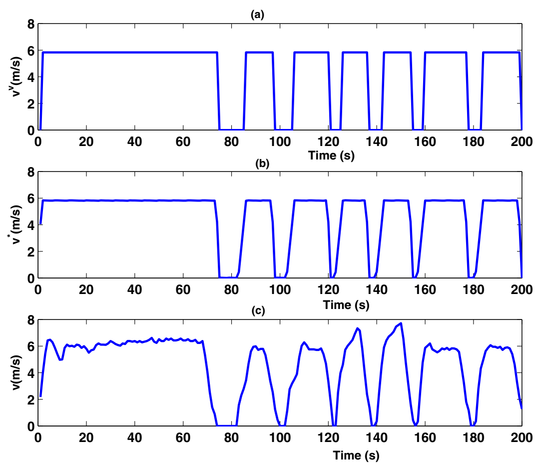

Fig. 4. One Lap Speed Profiles: (a) Speed profile Limit; (b) Optimal driving cycle; (c) Exeperimental driving cycle.

B. Global Energy Consumption Planning Validation

The speed limit profile is shown in the graph (a) of Fig. 4 for one lap. Using v^v, the driving cycle v^* (graph (b) of Fig. 4) is obtained by solving the optimization problem with the dynamic programming. The measured driving cycle for the first driver (Driver 1) is shown in the graph (c) of Fig. 4. We can observe that the optimal driving cycle is close to the speed limit profile compared to the measured one which has also several speed values exceeding the prescribed speed limit. To compensate for these overrun speed values, the human driver in most of the cases, decelerate quickly toward a stop sign, wasting energy if it is not adequately recovered.

Fig. 5 shows, for all drivers, the comparison of the mechanical energy profile using the driver driving cycle and the optimal speed profile. The optimal mechanical energy consumption is less than the mechanical energy when a human driver is controlling the truck. Furthermore, since the mechanical energy in this test scenario is a monotonically increasing function, we can conclude that the difference between the optimal energy profile and the human driver one will increase with time. Table II shows the energy saving obtained for each human driver driving cycle. The energy saving is represented by the difference between the total mechanical energy used with a human driver and the total energy obtained with the optimal driving cycle. With the propose method for energy planning, the optimal mechanical energy usage is lower than the energy obtained with the human drivers.

These results suggest that it would be better to plan the energy consumption of a vehicle with the propose method than using a driving cycle from a human driver in the best-case scenario where there is no traffic interference from other road users. Furthermore, this optimal profile can be used as a reference profile for the training of a hybrid electric vehicle

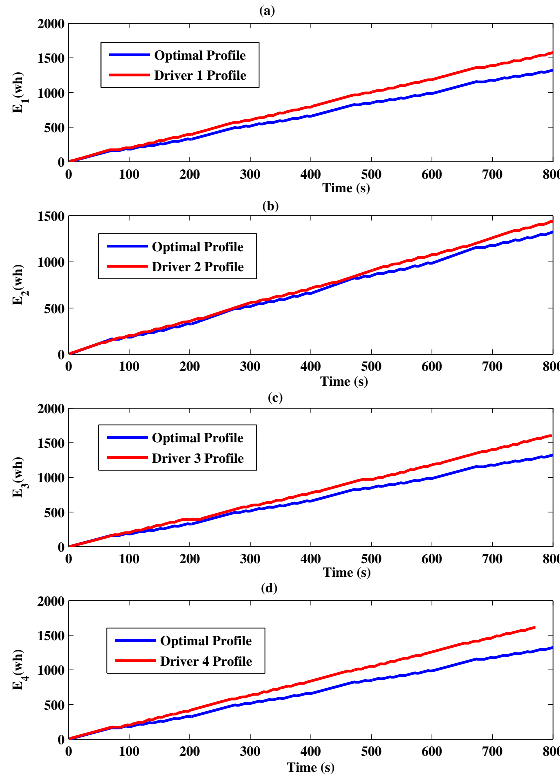

Fig. 5. Comparative Mechanical Energy Profiles: (a) Driver 1; (b) Driver 2; (c) Driver 3; (d) Driver 4.

TABLE II
COMPARATIVE ENERGY SAVING RESULTS: THE ENERGY SAVING RELATIVELY TO THE OPTIMAL PROFILE IS PRESENTED IN PARENTHESES.

Driving Cycle	Energy Saved (wh)
Driver 1	251.8(18.96%)
Driver 2	85.0(13.93%)
Driver 3	273.1(20.56%)
Driver 4	281.4(21.19%)

power splitting system.

V. Conclusion

In this paper, a method has been designed in order to calculate the most efficient driving cycle on a given trip. The objective was to show how it is possible to use the data extracted from a Geographic Information System in order to obtain useful informations for the energy consumption planning. The algorithm is formulated as an optimal trajectory tracking problem and the solution was obtained using the dynamic programming. On a given trip, the mechanical energy consumption obtained with a human driver is compared with the energy consumption obtained with the optimal driving cycle calculated by the method. These first results show a consumption reduced up to 21% with the optimal speed profile.

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