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Driving cycle and road grade on-board predictions for the optimal energy management in EV-PHEVs

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Abstract

The prediction of the driving cycle (vehicle speed profile versus time) and the road grade cycle (road grade profile versus time) can improve a variety of vehicle functions, especially the energy management of HEVs and PHEVs. The variability of the driving conditions (environment) together with the nonlinear and variable driver behaviour (driving style) makes the driving cycle 'on-board & real-time' prediction a highly complex task. This paper proposes an intelligent technique for the real time prediction of the vehicle speed and road grade profiles for the (selected) time horizon whilst the vehicle is in route. The proposed method uses an Artificial Neural Network which processes both the vehicle speed measurement (current and previous data samples) and some information related to the driving conditions present in the route, which could be obtained in advance from the new generation of vehicle navigation systems. The driving cycle and road grade on-board predictions allow the energy management system of HEV/PHEVs to achieve further reductions of fuel consumptions.

Keywords: Driving Cycle, Neural Network, Optimal Energy Management, NARX Network, Predictive Control

1 Introduction

During a trip, the instantaneous vehicle speed is influenced by the vehicle characteristics, by the driver's driving style (DDS), as well as by the driving conditions (DCOs) present in the road. In more detail, the vehicle speed profile versus time - also known as driving cycle - is function of the variables and factors shown in Fig. 1 [1]. These factors cause variability in the driving cycles recorded for the same vehicle making a route under different DCOs and/or DDS, see Fig. 2. The high variability of the DDS & DCOs makes the driving cycle (vehicle speed profile) on-board & real time prediction a highly complex task.

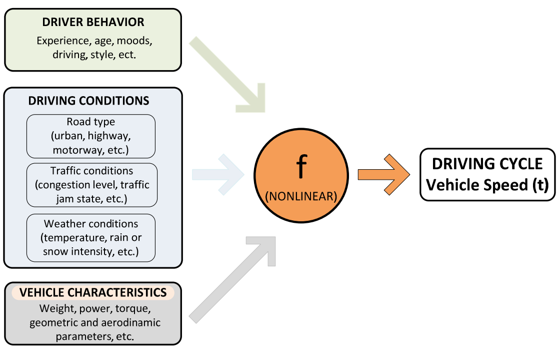

Figure1: Factors affecting the driving cycle.

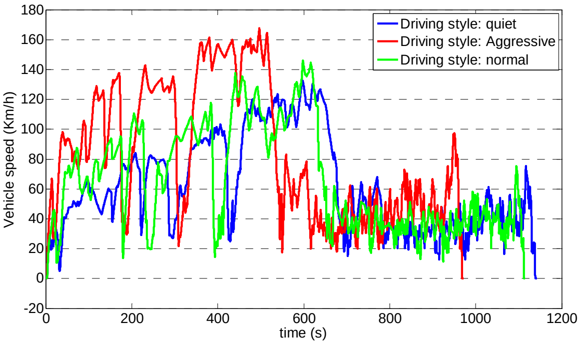

Figure2: A set of driving cycles obtained over the same route/trip

In HEV/PHEVs the way both mechanical and electrical power sources are combined lead to different hybridization architectures. Hybrid powertrains need a supervisory controller which manages the power split between the different power suppliers aiming to fulfil the vehicle and driver instantaneous power demands while some objectives such as the fuel consumption, energy efficiency, the emissions, or a combination of them are optimized [2].

Many strategies and methods have been proposed in the scientific literature for addressing the optimal power/energy management (O-EMS) in HEV/PHEVs [3]. The calculation of the global optimum in real time (whilst the vehicle is making the trip) is not possible since the objectives in the optimization problem are global and depend, among others, on the driving cycle and the road grade profiles, both unknown in advance.

Aiming to obtain high quality sub-optimal solutions for the O-EMS problem (power/energy splits) in real time, mainly two approaches have been proposed in the literature:

- Intelligent approaches based on the DCOs & DDS 'on-board & real time' recognitions followed by a fuzzy or expert energy management strategy which processes a set of rules containing the identified DCOs & DDS. Some examples can be found in [4, 7, 9].
- Optimization approaches based on the driving cycle 'on-board & real time' prediction. Once the driving cycle (speed profile) is predicted, different optimization solvers and methods are used for solving in real time the O-EMS optimization problem. An example can be found in [5].

This paper proposes an innovative technique to obtain - on-board, in real time and whilst the vehicle is in route - the prediction of the vehicle speed & road grade profiles for the (selected) next time horizon. At each selected sampling time (time-driven) or when the energy management system makes a request (event-driven) the predictions are updated (recalculated) in real time for the new time horizon (receding horizon). The method is based on an Artificial Neural Network (ANN) which processes the next information:

- The vehicle speed that is being recorded while the vehicle is in route.
- Some 'in advance' static information related to the road traffic signals and road grade (road information) that can be provided in real time from modern navigation systems integrating digital maps and Geographical Information System-functionalities (GIS).
- If available, some 'in advance' real time dynamic traffic information (traffic events, traffic state, weather state, etc.) obtained from modern navigation systems capable of integrating vehicle to vehicle (V2V) and/or bi-directional vehicle to infrastructure (V2I) advanced communication systems. Thus, the traffic state and events could be exchanged with the infrastructure or even with other vehicles that are making the same route.

The paper is organized as follow. In section 2 some methods and techniques used for the driving cycle modelling and prediction are reviewed. The proposed method for the driving cycle & road grade 'on-board & real time' predictions for the (selected) time horizon is described in detail in section 3. In section 4, some results are presented and discussed. The paper is finally concluded in section 5.

2 A review of methods

It is important not to confuse the term DCOs with the term driving cycle. As was introduced before, the DCOs refer to the set of external factors which define or characterize the environment through which the vehicle is circulating. Consequently, the driving cycle is the result of the movement of a vehicle-driver (as a whole) that is subjected to some variable DCOs when they are making a trip. Thus, the driving cycle (vehicle speed profile) depends not only on the DCOs but also on the vehicle characteristics and the DDS, as was introduced in section 1, see Fig. 1.

Although there is neither consensus nor standardization, the DCOs are usually composed by two variables when they are used for energy management purposes: the road type and the traffic congestion level. The values that these variables can take can differ depending of the authors and

applications, but it is very common to use the values 'urban', 'extra-urban', or 'highway-motorway' for the road type and 'low', 'medium' or 'high' for the traffic congestion level. Often, the DCOs are also defined by only one variable which can take a value among 1 to 9 corresponding to the DCOs characterizing nine of the eleven known driving cycles which were defined and proposed in [6].
Different research works and studies have been conducted aiming to make the 'online & real time' (on-board) recognition and even prediction of the DCOs. Among others, one can stand out those using the processing of the vehicle speed profile that is being recorded while the vehicle is moving [4, 7, 8, 9]. In most of these works the authors obtain some - among those identified in [1] - statistical parameters from the speed profile and then infer the DCOs values using different classification techniques such as ANNs, Support Vector Machines (SVM), etc. Furthermore, the DDS are also recognized in [7] by using a fuzzy inference system in which the rules and membership functions are constructed from the statistical processing of the vehicle speed profile. Some possible values for the DDS can be: 'quiet or calm', normal', 'aggressive', etc., and once recognized it could be considered in the energy management strategy, as it occurs in [7]. Another method can be found in [13] where the authors use the standard deviation of the vehicle speed's second derivative (jerk analysis) to infer the DDS.
However there are few studies in which a direct method for the vehicle speed profile 'on-board & real time' prediction is proposed. In [11] the authors propose a technique for the speed profile prediction in the trip domain (vehicle speed as function of the distance travelled) by gathering a simple data base constructed from historical data recorded over a determined commuting route. A clustering algorithm together with a state transition diagram is used for the driving pattern prediction.
More recently in [5], the authors propose a method for modeling a trip's driving cycle by using a GIS and a data base containing historical information about the traffic's state for that route. Once the trip's beginning and final destination are defined, some information received from the GIS such as road speed limits, traffic lights position, etc., are processed. Starting from this information, first a simple and segmented driving cycle is constructed in which the vehicle speed value matches the speed limit values and the accelerations/decelerations are considered as constant. The simple driving cycle is then modified by using the traffic's state historical data base -if it is available for that trip- by using some traffic modeling techniques.
It is important to notice that the vehicle characteristics (vehicle type) and the driver driving style is not taken into account in both methods, thus penalizing the accuracy in the speed profile (driving cycle) prediction and therefore the benefits obtained from the O-EMS. In fact, the driving style has a great impact on the vehicle fuel consumptions and emissions as it is shown in [10] and [12].

3 Driving cycle and road grade predictions.

As it was introduced before, the factors affecting the driving cycle are: the type & characteristics of the vehicle, the driver's driving style and the DCOs present in the route. The basic concept behind the proposed method is derived from the general concept of control system theory in which the controller response and some measurable or un-measurable disturbances can cause a deviation between the system output (controlled variable) and its desired response (reference).
By analogy, in the problem at hand the controlled system is the vehicle, the controller is the driver, the controlled variable is the vehicle speed where the system response is therefore the speed profile/driving cycle (speed versus time), and the desired system response is the desired/expected vehicle speed profile - reference driving cycle - from a point of view of the traffic control/management system (who regulates the road speed limits, static and dynamic traffic signals, traffic lights, etc.), see Fig. 3.

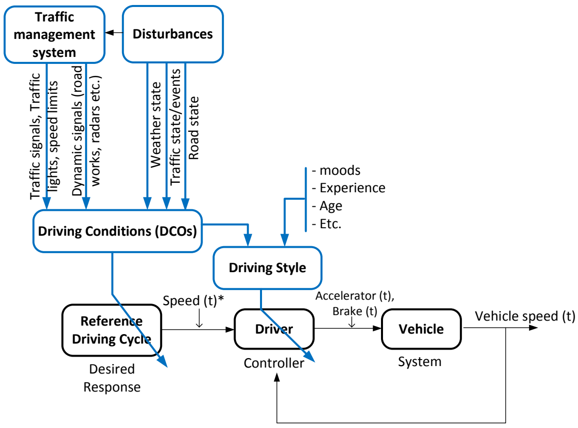

Figure3: Basic concept. Control system diagram.

Some disturbances such as the traffic state, traffic jams, road works, the weather state, or the road state among others, can change the DCOs thus changing the real road speed limits and even the driver driving style, so the system response (vehicle speed profile) will be affected.

The proposed method is based on the hypothesis of considering that a reference driving cycle (reference speed profile) is constructed and adapted in 'real time' and 'in advance' by using some information about the route's DCOs. This information could be provided from a new generation navigation system installed on the vehicle thus incorporating:

- Digital maps and geographical information functionalities in order to provide 'in advance' some information related to the speed limits and traffic signals which are present in the next time-horizon (electronic horizon) according to the route that is being made [14].
- A communication system for receiving data from a Central Data Server for providing 'in advance' real time traffic information related to the traffic state (density, congestion level, etc.), traffic events, speed limits due to road works, traffic jams, weather state, etc., for the next time-horizon according to the route that is being made [15].

The deviation between the real vehicle speed and the speed reference of the reference driving cycle (obtained as explained before) is assumed to be caused for the own driver's driving style as well as for the type & characteristics of the vehicle. Therefore, the problem presents two challenges which are treated separately in this work. The first treats to obtain -in advance and in real time- a reference driving cycle according to the information that is being received about the DCOs. The second treat to model the influence of the driver & vehicle and then obtain the final driving cycle or speed profile prediction for the next time horizon. For that, a nonlinear processing (through an ANN) of the vehicle speed deviation profile (with respect to the speed of the reference driving vehicle) that is being obtaining whilst the vehicle is running, is proposed. The technical details for both challenges are respectively described in next subsections.

3.1 Obtaining the reference driving cycle

The Reference Driving Cycle (RDC) profile is constructed in real time by using the information received from the GIS based navigation system. It has a staggered form with speed constant sections or intervals and infinite acceleration/deceleration joining the speed sections. It is important to note that the RDC is a speed profile defined on the trip domain, i.e., it is a vehicle speed profile versus the distance travelled. In fact, the GIS navigation system only could know in which kilometer point there are changes on speed limits (speed limits traffic signals). The speed value for each trip section or interval is the speed limit imposed by the traffic regulator for that section. A Base Reference Driving Cycle (BRDC) is first constructed according with the road traffic speed limits existing in the road on which the vehicle is travelling (positions on the trip domain & speed limit values). Thus, the BRDC would be the driving cycle imposed and/or recommended by the traffic management system (traffic regulator), and would be also ideal or optimal in the sense that it would permit to make the trip employing the minimum time but fulfilling the speed limits restrictions present in the road (legal driving cycle). Obviously it is not possible and improbable to satisfy this BRDC because, among others, the vehicle-driver as a whole cannot impose infinite acceleration/ deceleration on the vehicle speed as well as the driver can bypass the traffic regulations (these effects are treated in subsection 3.2). An example of a constructed BRDC for a trip is shown in Fig. 4, where the route's information was extracted from a digital map.

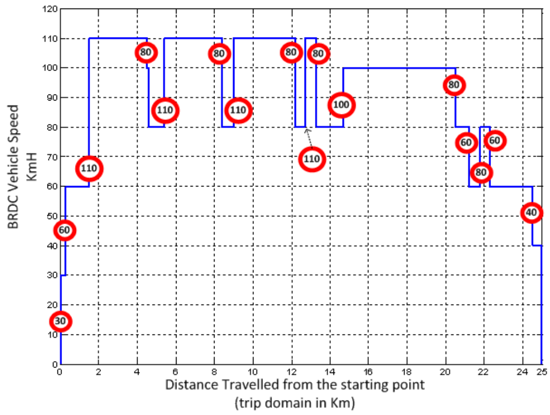

Figure4: Example of a Reference Driving Cycle.

The BRDC could be then updated according to real time traffic information if it is available (traffic state, events, dynamic traffic signals, weather conditions, road states, etc.). This information could be received via communications from the Traffic Management Data Center or even from others vehicles making the same route. For example, the Traffic Data Center could inform the vehicle about the real speed in a road/trip interval in which there is a high traffic congestion level sending the next information: [initial position, final position, current speed value], or the vehicle could be also alerted about the position (on the trip domain) in which the traffic is stopped due to a hard traffic jam. Therefore, the final RDC is constructed from the staggered BRDC by updating its speed values according to the real time traffic information received (traffic state and events) if this functionality is available.

The RDC could be entirely constructed at the beginning of the trip if all the information of the route is a priori known and the traffic state is normal and fluid. However the RDC is normally constructed and updated in real time by using the information received from the GIS navigation system while the vehicle is in route.

3.2 Modelling the behaviour of the driver & vehicle.

As it was appointed before, the RDC profile is defined on the trip domain i.e. vehicle speed as function of the distance travelled or the kilometer point. The variability of the driver-vehicle (as a whole) causes that the RDC cannot be fulfilled due to the reasons explained bellow:

- The vehicle-driver as a whole cannot get infinite speed accelerations/decelerations. The vehicle, in function of its characteristics, will have different acceleration/deceleration power.
- The driver reacts differently (as a function of its actual driving style) to a change in the speed of the RDC profile. For example, a driver with an aggressive or sportive driving style accelerates quite before of reaching the kilometer point where an increment of the RDC speed occurs. This is possible due to the driver's visual range. However a quiet driver (calm driving style) accelerates softly just before (or even after) the kilometer point where the speed increment occurs.
- The driver usually does not maintain the speed constant in the RDC's constant speed sections. A driver with an aggressive driving style will usually exceed the speed of the RDC and the vehicle speed will have also more oscillations than a driver with a calm driving style.

Consequently there is a speed deviation between the vehicle speed (final driving cycle) and the RDC in the distance/trip domain, in which the speed deviation profile (trending) is quite different in function of the vehicle behavior and the driver's driving style during the trip (which can even change along the trip).

The proposed model for approaching the RDC vehicle speed deviation with respect to the RDC - from now on (RDCSD) - which is caused from the driver-vehicle behavior as a whole, is given in (1), where $RDCSD_{dk}$ is the speed deviation for the k (actual or present) sampling step (in the distance/trip domain), DSN is the number of previous data samples of the own RDCSD that are considered in the model, $V^{RDC}{}_{k}$ is the RDC speed for the k (actual) sampling step in the distance/trip domain, FSN is the number of k-step ahead of the V^{RDC} that are considered in the model, and f_{NL} is a nonlinear function. It is important to note that all variables in this case must be referenced in the distance/trip domain, so if the vehicle speed is measured by using a time-driven procedure an easy domain transformation must be done (from time domain to distance domain) to obtain the vehicle speed as function of the distance travelled.

$$\begin{aligned} RDCSD_{d_{k+1}} = f_{NL}(&RDCSD_{d_k}, RDCSD_{d_{k-1}}, ..., \\ &RDCSD_{d_{k-DSN}}, V^{RDC}_{k+FSN}, V^{RDC}_{k+FSN-1}, ..., \\ &V^{RDC}_{k}, V^{RDC}_{k-1}, ..., V^{RDC}_{k-DSN}) \end{aligned} \quad (1)$$

According to the model presented in (1), the RDCSD is function of its own 'DSN' previous data samples (from $RDCSD_k$ to $RDCSD_{k\text{-}DSN}$) and of the 'DSN' previous data samples & 'FSN' data samples ahead of the RDC speed ($V^{RDC}{}_{k\text{-}DSN}$ to $V^{RDC}{}_{k+FSN}$). The fact of using the 'FSN' k-step ahead of the RDC is due to the need to consider the driver's visual range distance (the driver perceives in advance the traffic and can react differently depending of his driving style). The 'DSN' previous data samples for both the RDC and the RDCSD give us a picture of the driver-vehicle behavior in the recent past of the trip/route that is being done. Therefore observing and processing the speed deviation with respect his corresponding RDC in the recent past, it could be possible to estimate the evolution of the speed deviation in the distance/trip domain for a near future - in which its RDC is a priori known - by assuming that the driver-vehicle behavior will not change significantly with respect to which it had in

the recent past. However it is practically impossible to obtain a mathematical expression for the nonlinear function f_{NL} in (1) mainly due to the high nonlinearities and high variability present on the driver behavior.
In this work, a nonlinear autoregressive neural network with exogenous inputs (NARX) [16] is proposed as nonlinear function f_{NL} for approaching the RDCSD. The NARX is previously trained by using real examples (driving cycle, reference driving cycle) recorded from the vehicle-driver for different trips or routes. As the NARX models the influence of the vehicle-driver, it is not very dependent of the trip/route, data logged on different trips can be used for training the NARX.
The NARX will work recursively along the prediction horizon (defined now in the distance/trip domain) obtaining the prediction of RDCSD* for the next trip-domain horizon (Hd).

3.3 Obtaining the driving cycle and road grade predictions.

Once the RDCSD* prediction has been obtained by using the NARX model, the prediction of the driving cycle for the same (trip-domain) horizon is directly obtained by adding the RDC profile speed values (that must be known in advance by using the GIS information) to the RDCSD* speed deviation values along the horizon (Hd), see (2), where DCDD* is the prediction of the driving cycle in the distance domain, and Δd the resolution selected for the distance domain discretization (distance between two samples) .

$$\begin{aligned} &\mathrm{DCDD}^*(k) = V^{RDC}(k) + \mathrm{RDCSD}^*(k) \\ &\forall k = k, (k+1), (k+2), \ldots, (k + Hd/\Delta d) \end{aligned} \tag{2}$$

The driving cycle prediction on the time domain (DCTD*) can be obtained from the DCDD* by making a domain transformation (from distance to time) using the own DCDD* speed values (3). Thus, the vehicle speed profile prediction as function of the time is finally obtained.

$$\begin{aligned} &\mathrm{DCDD}^*(k) \Rightarrow \mathrm{DCTD}^*(t) \\ &\Delta t^*(k->k+1) = \frac{\Delta d}{\mathrm{DCDD}^*(k)} \\ &t^*(k+1) = t^*(k) + \Delta t^*(k->k+1) \\ &\forall k = 1,2,3,\ldots, Hd/\Delta d \end{aligned} \tag{3}$$

A block diagram describing all the steps for obtaining the driving cycle prediction is shown in Fig. 5.

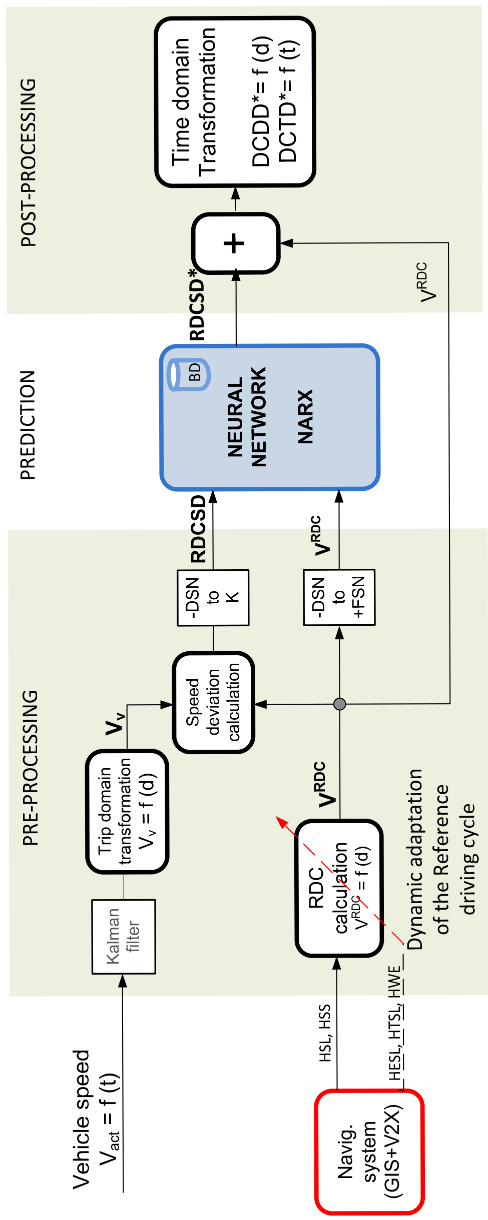

Figure5: Driving cycle prediction block diagram.

The road grade profile prediction in the distance/trip domain can be known directly in advance because could be received from the GIS navigation system for the next trip-based horizon. Thus, for obtaining the road grade profile prediction but in the time domain is necessary to make a domain transformation (from the trip domain to the time domain). It is not difficult to implement this transformation since the vehicle speed profile prediction has been just before obtained.

4 Results

Aiming to check the performance and accuracy of the proposed method, a data acquisition and logging system (DA&LS) was installed in a vehicle SEAT Ibiza. The DA&LS was able to record in real time: the speed and position of the vehicle while the vehicle was in route. The selected DA&LS also incorporated for obtaining a video-film (synchronized with the speed and position measurements) of the trip/route driving environment, as can be seen in Fig. 6. Once the trips were concluded, the final driving cycle was obtained by post-processing the recorded vehicle speed & position. In addition, the RDC was constructed by the post-processing of the video-film (traffic signals, speed limits, traffic state, etc.). The trips were done between the towns of Martorell and San Joant Despí in Barcelona.

Figure6: Picture of the video-film captured in one of the trips. Courtesy of SEAT-Technical Center.

Ten pairs of final driving cycles (in the time domain) and RDCs (in the trip domain) were recorded. Eight of them were used to train the NARX and the rest were used for testing purposes. The NARX configuration was:

- Multilayer network with one hidden layer composed by 15 neurons of 'tang-sigmoide' function type. The output layer was composed for a neuron of 'pure-lin' function type.
- The trip distance discretization steps, Δd, was set to 0.05 Km.
- The DSN was set to 40, so the past recent size was 40 x 0.05 = 2 Km
- The FSN was set to 3, so the near future (equivalent to the driver's visual range) was 3 x 0.5 = 150 m.
- The method used for training was the Bayesian Regularization in order to exploit its generalization capabilities [6].

Once the NARX was trained a testing with the examples that were not used for training was carried out. Results are displayed in Fig. 7, in which the driving cycle prediction was obtained at the kilometer point 2.5Km and the prediction horizon (on the trip domain) was set to 13Km. The route was known so the prediction horizon was large.

The precision or mean error in the driving cycle prediction was less than 4 Km/H for both cases, and was calculated from the sum of the absolute errors in the considered horizon window divided by the number of samples in the given horizon.

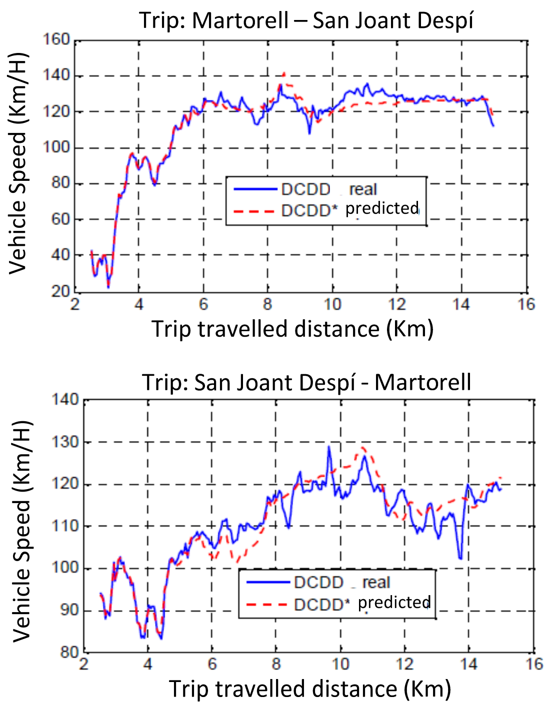

Figure7: Prediction results.

In order to test the proposed driving cycle prediction system in real time while the vehicle is in route, the algorithm and the NARX were implemented on a Real Time Embedded System (RTES). The RTES was installed on-board the SEAT Ibiza and was connected to the Vehicle Control Unit (VCU) via the CAN bus. The VCU vehicle speed measurement was sent to the RTES via the CAN bus communication. Results are displayed on Fig. 8.

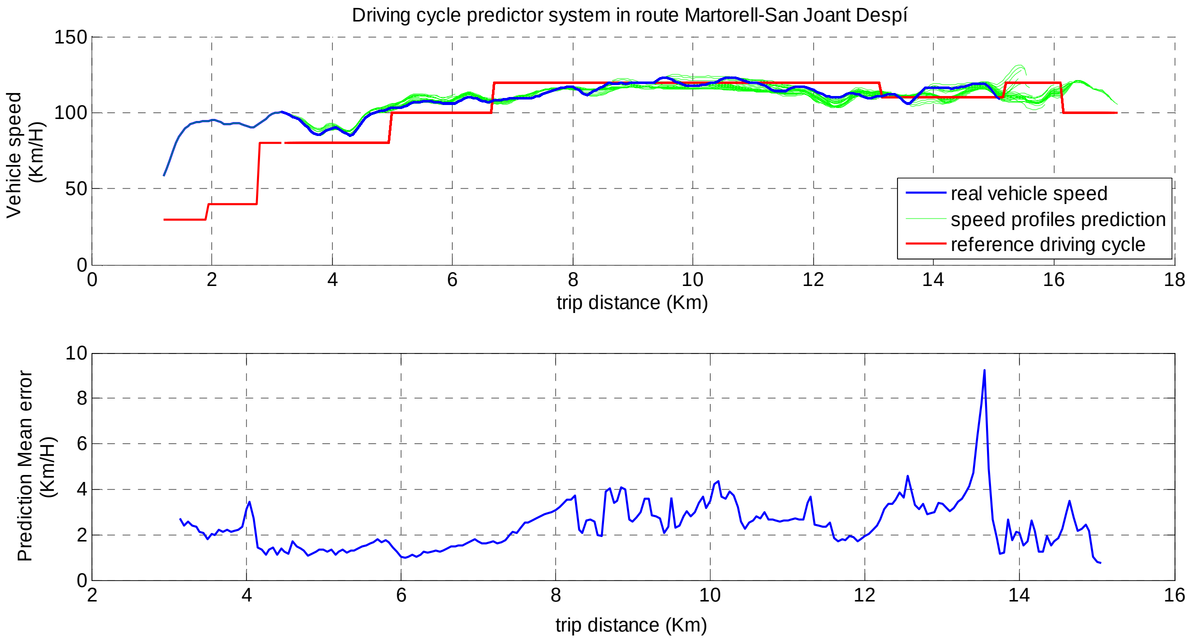

Figure8: Prediction results on-board and in real time.

The prediction horizon was set to 3 Km, and the predictions were triggered in real time each 0.05 Km while the vehicle was in route, so many predictions speed profiles of size 3Km Km were obtained (green color in the first graph of Fig. 8). The RDC is displayed in red color and the real vehicle speed in blue color. The mean error for each predicted speed profile is shown in the second graph of Fig. 8, usually lower than 4 Km/H. The testing for that trip was successful.

5 Conclussions

An innovative technique to obtain - on-board, in real time and whilst the vehicle is in route - the prediction of the vehicle speed & road grade profiles for the (selected) next time horizon is presented in this paper. At each selected sampling time (time-driven) or when the energy management system makes a request (event-driven) the predictions are updated (recalculated) in real time for the new time horizon (receding horizon). The method is based on an Artificial Neural Network of type NARX which processes: the vehicle speed that is being recorded while the vehicle is in route; some 'in advance' information related to the road speed limits and road grade (road information) that can be provided in real time from modern navigation systems incorporating digital maps and geographic information functionalities; and if available some 'in advance' real time dynamic traffic information (traffic events, traffic state), obtained from modern navigation systems capable of integrating in addition vehicle to vehicle and/or bi-directional vehicle to infrastructure advanced communication systems.

The driving cycle prediction system has been tested on-board in a vehicle (courtesy of SEAT) while travelling for a route around the Martorell area with satisfactory results.

The energy management strategies of Plug-in HEV with parallel or series powertrain structure (Range Extender) reach the lowest fuel consumption by using a Charge depleting strategy (CD). This CD strategy is most efficient when the future trip is known a priori. But also the prediction data of shorter predictions horizons (and therefore higher exactness of the predicted data) can attribute to lower fuel consumption [17].

Acknowledgments

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