GPS data integration to reduce driving emissions of MHEVs in real operating conditions

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Abstract. Increasingly emission reduction requests and environmental pollution cut require improved optimization of current transportations. Control strategies and latest vehicles technologies developed in the automotive industry must be optimized, taking into account more information is possible from cars sensors to save energy and reduce emissions. The paper presents a possible strategy for reducing emissions with integration of GPS data in a Mild Hybrid Electric Vehicle simulator. In this study, real GPS data are evaluated to improve the system and introduce real environmental conditions in the system. The data obtained are analysed selectively in the paper. This paper is aimed to investigate the impact of real conditions on fuel consumption. Through theoretical analysis, the conclusion will be drawn that GPS technology is attractive to reduction of emissions.

1. Introduction
In recent years, the rapid automotive market development increased the number of hybrid vehicles. The hybrid vehicles, compared to other fuel vehicles, have high efficiency and excellent emissions performance[1,2]. The emissions are one of the most critical factors to take into account during the intensive study of Mild Hybrid Electric Vehicles (MHEVs) [3-6]. Last decade presented different studies of MHEVs from different points of view such as modelling, systems simulation, safety, reliability, fuel consumption; all ways have been investigated to reach new and optimized solutions on environmental pollution cut. Furthermore, since the automotive field has been introduced the hybrid car, new control approaches had to be adopted [7-12]. However, the control strategies to apply to these systems are very complex in that they must consider an increasing number of variables and non-linearities. The automotive industry requests more and more real-life conditions in the simulation of the vehicle. This characteristic complicates the modelling approach and needs evidence. Nowadays, vehicles are equipped with different sensors [13-16]. Based on the data from GPS sensor and measuring the position of the car, embedded controllers could better understand the dynamical position of the car and compute the action to apply. The precision of the new sensors distributed inside the cars has made it possible to extend the information available from the vehicle dynamics and guarantee better performance, maintaining the focus on the reducing of emissions. Also, the vehicles most considered for the production and commercialization are the MHEVs, that use two types of power sources, engine and electric motor. Previewing characteristics of the near road to face could allow deciding which type of engine claim and improve the fuel economy and emission reduction. The integration of GPS sensor into the control loop could help for tracking and managing the vehicle [13], but an accurate simulator is needed to design the complete control strategy. In this paper, an MHEV is modelled and simulated. Also, respecting [3], a GPS sensor, including real data, is integrated into the system to investigate the impact of the real driving condition on fuel consumption in the simulated system. The simulator has been validated comparing behaviour on real situations versus World Harmonized Light-duty Vehicles Test Procedure cycle (WLTP) in examine the fuel consumption and emissions.
2. Proposed system design

Authors designed an improved simulator starting from the one on [3] and with the integration of the GPS information. The GPS information could be loaded from a previous survey or they could be obtained in real-time by an external serial connection. The system is designed taking into account the limitations of Government regulations and of a complete MHEV vehicle with all subsystems devoted to the motion. The overall aim of considered laws is the reduction of transport emissions and energy consumption. The benchmark levels for cars for 2025 will be 15%, and for 2030 35%. The increased focus on monitoring of ‘real-drive’ emission, from January 2019, justify the importance of having real data into the simulation.

2.1. Vehicle system

The system has been modelled in Matlab Simulink environment. The designed infrastructure of parallel-series MHEV includes an electrical system level with DC-DC converter and battery models, engine model with shaft and inertia and full vehicle dynamic model. The configuration of the vehicle, chosen for this simulation case, is a P2. The e-vehicle model is explained in section III of [3].

2.2. GPS technology

Recent trends in automotive industries to reach highly accurate position information and improve safety have led to introduce positioning systems. The GPS is an attractive technology to track car position and manage it. However, this technology requests a driving cycle with some features[13]:

1. Exclude short cycle;
2. Organize the direction of trajectory data;
3. Smooth the speed;
4. Divide a trip into several segments;
5. Exclude traffic influence;
6. Repeat the same route.

A GPS-recording vehicle trajectory P, with R data points, is mathematically defined in the simulator as:

\[ P_R = [(p_1, t_1), (p_2, t_2), \ldots, (p_R, t_R)] \]  

where P represents a trajectory and p represents a data point on the trajectory with three variables: latitude, longitude and altitude; R is the total number of the data points of trajectory P. Each data point of the trajectory is recorded at timestamp t. The GPS recording interval remains the same for all trajectories of all vehicles in this study (1 second), therefor the timestamp feature is excluded from the dataset for computing reduction. A simplified data point is expressed by the following:

\[ p_R = [(lat_1, long_1, alt_1), \ldots, (lat_R, long_R, alt_R)] \]  

Supposing vehicle at the same altitude during the simulation, the Euclidian distance from \( p_R \) is calculated with the following formula where the time from one data point to the next is 1 second:

\[ \text{dist}(p_t, p_{t+1}) = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2} \]  

Where \( x_r \) is the \( r^{th} \) latitude and \( y_r \) is the \( r^{th} \) longitude.

2.3. Driving Cycles

Three real driving cycles, based on GPS track, was created with a real car and chosen for this study, which includes real driving data from different conditions. The three cycles have been compared with the World Harmonized Light-duty Vehicles Test Procedure cycle (WLTP), a global, harmonized standard for determining the levels of CO\(_2\) emissions and fuel consumption of traditional and hybrid cars, used in European Country since 2015. The three real driving cycles and WLTP are summarized in Table 1. The driving cycle WLTP, Figure 1, is chosen as first to be compared with the others. The second is a Cycle in Urban Area (CUA, Figure 2), with variable speed. The third drive cycle, Cycle in
Extra-urban Area (CEA, Figure 3), is an extra-urban driving cycle that includes high-speed maintained for all life-time-cycle. The fourth, Cycle in Urban and Extra-urban Area (CUEA, Figure 4), is an urban and extra-urban driving cycle.

**Table 1.** Driving cycle description.

| Cycle  | Distance | Time | Average speed | Standard Deviation |
|--------|----------|------|---------------|--------------------|
| WLTP   | 23266    | 1800 | 46.5          | 36.03              |
| CUA<sup>a</sup> | 18820    | 1138 | 59.48         | 22.03              |
| CEA<sup>b</sup> | 47800    | 1470 | 117.06        | 18.69              |
| CUEA<sup>c</sup> | 43750    | 1928 | 81.65         | 25.08              |

<sup>a</sup> Cycle in Urban Area.
<sup>b</sup> Cycle in Extra-urban Area.
<sup>c</sup> Cycle in Urban and Extra-urban Area.

3. **Simulation results and discussions**

The GPS sensor is placed in a car with a manual shift. A car with a cruise control to maintain the same speed for a long time has been chosen. These GPS has been logged every one second. The altitude is correcting with EGM96 (Earth Gravitational Model), a geopotential model of the Earth's surface consisting of a sum of spherical harmonics up to 360° order and degree. The obtained GPS signal consists of a string with different information. For this study has been considered three main variables: latitude, longitude and altitude. The tests are conducted in areas with good GPS reception quality, and this has assured to provide the required signal accuracy. In this case GPS data give a good instantaneous measurement of vehicle speed. The fuel consumption and the emission in the driving cycles is shown in Table 2. The formula for the emission is described in [3]. Table 1 shows the standard deviation. The data is examined to relate the speed standard deviation of a cycle with the emission and distance. The figures 1-4 present the speed in km/h of the track and time in seconds.
Figure 2 CUA driving cycle

Figure 3 CEA driving cycle
4. Conclusions
This paper shows the work done integrating the GPS data into an MHEV simulator. The work presented how the GPS provides a more accurate vehicle speed profile and it allows real driving emissions analysis. The actual simulator has a PI controller inside the loop that manages the use of the electric and the traditional traction. With the improved scheme a control supervisor could be added in order to improve fuel consumption and emissions in real-time.

5. References
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