CO_2 Impact of Intelligent Plug-in Vehicles

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Abstract: - Information and Communication Technologies can play a very important role in order to optimize the energy usage of hybrid and electrical vehicles and, thus, to reduce their environmental impact. In particular, vehicular communications can be exploited to spread information useful to predict future driving conditions and, then, future load power demand of vehicles. In the present investigation, the potentiality of ICT to reach this goal has been analyzed numerically with respect to a plug-in hybrid electric vehicle and a battery electric vehicle. The simulation of the driving scenario and the prediction of future speed profile on board of a vehicle have been obtained with the use of a vehicular traffic simulator (SUMO). CO_2 emissions were calculated with at Well-To-Wheel approach with respect to realistic urban driving patterns.

Key-Words: - Plug-in vehicles, energy consumption optimization, ICT, WTW emissions of CO_2

1 Introduction

Since early 1900s, gasoline and diesel internal combustion engines have represented the most successful automotive powering systems despite their low efficiency, their emissions issues and the increasing cost of fuel. Their main advantage over both gas engines and Battery Electric Vehicles (BEVs) is the very high energy density of liquid fuel that allows long driving ranges with small (and light-weight) storage tanks and safe and fast refueling processes. Moreover, gasoline and diesel fuels have an established infrastructure of distribution that is difficult and very expensive to replicate for other energy sources.

Environmental issues, energy crises, concerns regarding peaking oil consumption and the expected increase of number of cars in developing countries have eventually encouraged research into alternative energy sources. However, they are still unable to penetrate the market for several technological limitations.

The main drawback of BEVs resides in the batteries. They are still too expensive, too bulky and heavy (due to their low energy density). Moreover, they have an unsatisfactory life cycle and require long recharging times. Vehicles using fuel cell (FCV) a very clean fuel conversion system have technologic drawback even higher. They add to the problems of a BEV, the use of a very light gaseous fuel that has severe limitations in terms of producing process [1], storing system, safety and distribution infrastructure. Thus, they are not to be considered as a viable way for eco-mobility in the next future [2].

Hybrid electric vehicles are characterized by the presence of two different typologies of energy storage systems: usually a battery and a gasoline or diesel fuel tank. HEVs have no limitation of range with respect to conventional vehicle and use the existing distribution infrastructure. The main advantages of HEVs are: the flexibility in the choice of engine operating point and the possibility of downsizing the ICE and so obtaining a higher average efficiency. Moreover, the engine can be turned off when the vehicle is arrested (e.g., at traffic lights) or the power request is very low (reduction of idle losses).

PHEVs can be considered either as BEVs that can be run in hybrid mode when the state of the charge (SOC) of the batteries is low or as HEVs with batteries that can be recharged from the electricity grid. They are characterized by the use of much larger battery packs when compared with standard HEVs. The size of the battery influences the All Electric Range (AER), an important design parameters of PHEVs that is defined as the number of miles they vehicle can run in pure electric mode on the UDDS cycle. A vehicle is classified as PHEVXY if AER is XY miles.

PHEVs require fewer fill-ups at the gas station than conventional cars and have the advantage, over HEV, of home recharging.

BEVs, HEVs, and PHEVs can partially recover energy from brakes by inverting the energy flow from batteries to wheels through the electric machine.

Simpson [3] presented a comparison of the costs (vehicle purchase costs and energy costs) and benefits (reduced petroleum consumption) of PHEVs relative to HEVs and conventional vehicles. On the basis of his model, Simpson found that PHEVs can reduce per-vehicle petroleum consumption. In particular, reductions higher than 45% in the petroleum consumption can be achieved using designs of PHEV20 or higher (i.e. vehicles containing enough useable energy stored in their battery to run more than 20 mi (32 km) on the UDDS cycle in electric mode according to the previous definition of AER).

The study of Simpson [3] underlined that from the economic point of view, PHEVs will be a competitive technology is the cost of petroleum will continue to increase and the cost of the batteries will decrease.

Because of different characteristics of multiple energy sources, fuel economy and environmental impact of hybrid vehicles mainly depend on a proper power management strategy. [4].

Generally speaking, the environmental impact of a vehicle has to be determined with a “well to wheel” (WTW) approach. From a “tank to wheel” (TTW) point of view, a BEV does not produce either pollutant or greenhouse gases. The emissions of pollutant and CO_2 in the WTW processes depend on the primary source and the technology used to generate electric energy at the grid. The well-to-wheel CO_2 emissions of a FCV can be equal to those of a diesel engine vehicle if it uses hydrogen produced from non-renewable energies sources [5].

In a hybrid vehicle, the local emissions of CO_2 and pollutant strongly depend on the management strategy used to select at any time the best energy source to deliver the power required at the wheel. Moreover, recent studies have shown that driver style, road type and traffic congestion levels impact significantly on fuel consumption and emissions [6],[7].

The possibility of estimating the future driving profile (speed and related power demand) is a key issue in the development of hybrid vehicles. In fact, the supervisory controller of a HEV could use the future speed profile to optimize the power split in a future time window in order to minimize fuel consumption, pollutant emission, battery usage and so on. Moreover, information about future can be used to activate the electric warming of engine and after-treatment devices. In this way they will be at the right temperature when the engine will be turned on and the exhaust gas flow will enter the after-treatment device.

In literature, a number of “auto-adaptive” techniques which try to predict future driving conditions based on the past ones presented been defined A possible approach is to predict the future driving conditions on the basis of past behavior [8] relying on the assumption that similar operating conditions will exist. But the future driving profile also depends on the instantaneous decisions which the driver will take to respond to the physical environment (driving patterns). For these reasons, the control strategies proposed in some schemes [8] incorporate the knowledge of the driving environment.

The present investigation analyzes the potentiality of plug-in intelligent vehicles in reducing overall CO_2 emissions by considering two test cases: a series hybrid prototype and an electric city car.

2 INTELLIGENT VEHICLES

According to Gusikhin et al. [9], a vehicle can be defined “intelligent” if it is able to sense its own status and that of the environment, to communicate with the environment and to plan and execute appropriate maneuvers. The first application of intelligent vehicle systems has been the increase of safety by providing driver assistance in critical moments. A combination of on-board cameras, radars, lidars, digital maps, communication from other vehicles or highway systems are used to perform lane departure warning, adaptive cruise control, parallel parking assistants, crash warning, automated crash avoidance, intelligent parking systems.

According to Mitchel et al. [10], it is necessary to transform the DNA of the automobile with four big innovations. The first one is design the vehicle on the basis of electric-drive and wireless communication rather than on internal combustion engine and stand-alone concept. The second innovation is the development of e-mobility platforms to share traffic and travel data. Third, integrate electric-drive vehicles with smart electric grids thus enhancing the use of clean and renewable energy sources. The forth innovation include the enhancement of car-sharing.

Markel et al. [11] studied the effect of integration between an electrified vehicle fleet and the electric grid in order to increase the amount of renewable energy used to power the electric vehicles by optimizing the timing and the power of the charging processes during the day. Different communication protocols have been considered and compared by Markel et al.[11] Intelligent Transport Systems like traffic management tools can have a direct effect on the emissions of CO_2 produced by the automotive floats [12]. According to Janota et al. [13], Intelligent Transportation Systems can reduce consumption and emissions by acting on the vehicle (by monitoring and controlling the engine), on the infrastructure (reduction of number/duration of congestions and stoppage, optimization of intersection, cooperative systems to avoid congestions) and on the driver (planning of ecologic routes based on real-time information, support to driver for economic drive).

Recently, Information and Communication Technologies (ICT) techniques have been proposed for gathering information about the vehicle routes and road conditions that could allow the evaluation of the future power request of the vehicle over a large time window. ICT techniques can be used to estimate the future driving profile, suggest low consumption behaviors to the driver, propose alternative route, communicate the position and the status of electric recharging stations, etc. [8].

Schuricht et al. [14] analyzed two active energy management measures. The first one, uses advanced traffic light, and communication systems to support the driver during intersection approaching. The second one explores the uses of information and sensor sources from the traffic telematics for the predictive online optimal control of hybrid vehicles.

2.1 Effect of driving condition prediction on a PHEV

The role of Intelligent Transport Systems in the improvement of PHEV performance and spreading of vehicles electrification is a research issue at the Center for Automotive Research at the Ohio State University. Starting from the awareness that traffic, weather and road conditions will be available in the next future through vehicle-to-vehicle and vehicle-to-infrastructure communications, the researchers at CAR emphasize the possibility of using this information for the tuning of the energy management controller in HEVs, predicting the future driving profile, signaling the availability of recharge stations, predicting the route and generating statistical information for modifying pre-stored maps.

In the paper of Tulpule et al. [15], the authors concentrated on the impact of available data on energy management in order to identify the most important factors on the actual fuel consumption of a PHEV. The factors analyzed in the investigation, named “Impact Factors”, derive from both weather information (temperature and humidity) and traffic information (status of traffic lights, presence of pedestrian, road events in intra-city highway and inter-city highway). Their importance on the performance of the ECMS strategy were evaluated on the basis of a large amount of data acquired on a Toyota Prius converted to plug-in mode. The plug-in Prius has been run for a total of 60,000 miles in the campus area of the Ohio State University and several parameters like GPS information, temperature, fuel consumption, battery SOC, etc. were collected along with time and date.

To study the effect of the driving patterns, Gong et al. [16] used a statistic approach to analyze real world profiles and derive information about average speed, speed limits, segment length, etc. These data were used to build a series of reference driving cycles by using the Markov chain modeling. The results of the investigation showed that driving patterns have a relevant effect on the performance of a plug-in HEV and that statistic values of acceleration have the largest impact of the tuning of the ECMS strategy.

2.2 Effect of driving condition prediction on a BEV

The main issue in the design of any electric vehicle is increasing the range calculated as the distance run by the vehicle with the battery discharged from full charge to 20% SOC on a specific driving cycle.

Driving cycles (or schedules) should provide a realistic and practical test for the range and the WTT emissions of electric vehicles. However, in the European scene the cycles tend to be rather simple, with periods of constant acceleration and constant velocity, no hills and no coasting. The official values of range given by manufacturers of electric vehicles are calculated according to these unrealistic cycles. Moreover, official range values can be referred to minimum accessory power request and normal clement weather.

Fig. 1 shows the battery depth of discharge of an electric vehicle according to the distance travelled in km as evaluated by Larminie et al. [17]. The depth of discharge is calculated in the hypothesis of normal clement weather, daytime conditions and in the case of colder conditions when in the dark (headlights and heater on). Note that the range, usually given as when 80% discharge is reached, drops from a little over 90 miles to about 70.

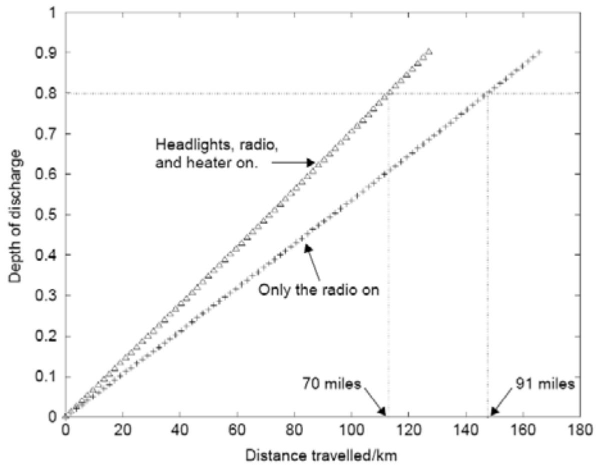

Fig. 1. An intelligent plug-in vehicle according to the CREA approach (adapted from [17])

The range of a electric vehicle also depends on the driving style, external factors like terrain and road condition and aging of the battery. The awareness that range can vary along the journey as well as across time can cause concern for the driver. This is known in literature as “range anxiety”. Among the strategies suggested by Nilsson, [18], to limit range anxiety, the following items show the relevant role of ICT:

- Accurate information about current range and status of EV;
- Suggestions on actions to best extend the range;
- Remote access of the vehicle status;
- Information about nearest charging station;
- Information about areas reachable by the EV;
- Suggestions based on personalized driving patterns.

3 The prediction/optimization scheme

The CREA idea of intelligent vehicle includes the possibility of sensing the traffic environment in which it moves to predict the future driving conditions (Ciccarese et al. [19],[20]). In particular, the vehicle is assumed to receive information from GPS, on-board sensors and vehicular communications. The scheme of the intelligent plug-in vehicle according to the CREA research center is shown in Fig. 2.

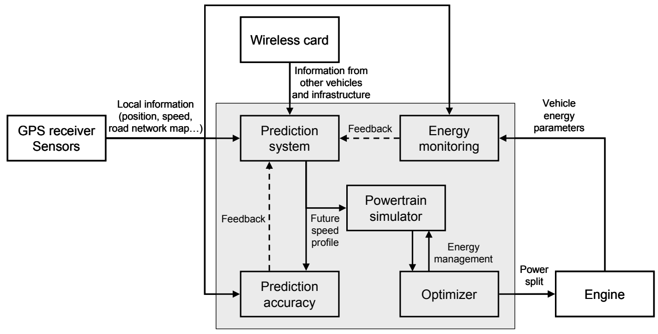

Fig. 2. An intelligent plug-in vehicle according to the CREA approach

The gray area in Fig. 2 represents the tools to be implemented on board. They include a prediction block, a power train simulator, and an optimizer..

The **prediction block** gathers information from GPS receiver and/or on-board sensors and status messages that surrounding vehicles and/or the infrastructure broadcast. Messages transmitted by a vehicle carry status information, such as position, speed, acceleration, etc., and, optionally, some information related to its route. Messages generated by the infrastructure, instead, carry not only the current status and the timing of traffic lights but also fundamental information about the position, the availability and the estimated CO_2 impact of the recharging stations.

All information can be used for statistical analysis according to the CAR approach or to take, at regular intervals, a snapshot of the traffic scenario in a given area like in the CREA approach. In this case, each snapshot is the input to a run of module which simulates the traffic dynamics over a certain time interval, whose duration is at most equal to the prediction horizon. In Ciccarese et al. [19], a modified version of SUMO software has been considered as on-board simulator.

The accuracy of the prediction method proposed by Ciccarese et al. [19] has been tested experimentally [20] in a augmented reality environment to simulate the presence in the Ecotecke campus of a certain number of vehicles able to communicate with the target vehicle. The experimental campaign showed that the inaccuracy of the prediction method is below 4km/h. In Fig. 3, a comparison is shown between the predicted and the actual speed profile of the target vehicle in a time window of 100s. More details about the experimental campaign can be found in Ciccarese et al. [20].

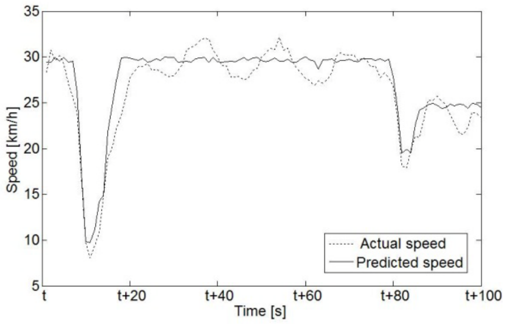

Fig. 3. Example of speed profiles obtained by the experimental environment

The **Power train simulator** block implements a model of the power-train. The block processes the output of the prediction system and calculates the related power demand of the predicting vehicle by considering aerodynamic force, inertial contribution, rolling force and grade force. Information from on board sensors (ambient temperature, asphalt conditions, tires pressure and temperature) can be used to correct the predicted load. Then, the block simulates the energy flows and evaluates the evolution of fuel consumption and battery SOC during the prediction interval.

Two different paradigms are usually considered to simulate a plug-in vehicle (Guzzella and Sciaretta, [5]). In the backward paradigm, the velocity of the vehicle is an input. According to the vehicle specification and speed values, the power request at the wheel is calculated. By means of static maps, the energy consumption of both engine and batteries is calculated according to the selected energy management strategy. If the power-train is not able to meet the cycle requirements, the acceleration is reduced and the vehicle diverges from the driving cycle.

In a forward or dynamic model, the power requested by the driver through the acceleration and braking pedals is used as input to evaluate the acceleration and the vehicle speed. This kind of model is used for the development of the control systems, while the backward method is best suited for analysis and evaluation of the energy and power flow in the vehicle driveline. Thus, a backward model is considered in the proposed scheme.

In the case of hybrid electric vehicles, the energy management block implements the **supervisor control** system which defines, at each time, the power split between the fuel conversion system (engine/alternator in a series HEV) and the electric storage systems (generally batteries) with the constraints that the sum of the power extracted from each energy source must be equal to the total power requested at the wheels. In the case of battery vehicles, this block is not required since there is only one energy storage system (the battery).

Different approaches for the optimal power management of a Hybrid Electric Vehicle were classified by Serrao [22] as:

- Heuristic Control Techniques,
- Numerical Optimization,
- Instantaneous Optimization,
- Analytic Optimal Control.

Heuristic Control Techniques (HCT) are often rule-based, e.g. given a set of conditions for the vehicle in terms of SOC, available power, engine temperature and required power, the HCTs decide the best working point of the vehicle in terms of power split, working on discrete maps.

Numerical Optimization uses Bellman's Principle and, in general, Dynamic Programming.

In the instantaneous optimization approach, a global minimization problem is solved by considering a sequence of local minimization.

The analytic optimal control naturally leads to a global optimal solution by using a simple mathematical model for the power-train, with low computational burden. This guarantees a real-time optimization.

Any of these techniques can take advantage of the knowledge of the future driving cycles ([23]).

The system also includes a block, named **Energy monitoring**, which monitors the energy parameters of the vehicle (engine efficiency, level of gasoline in the tank, battery SOC, etc.) and evaluates the effectiveness of the energy management strategy

Another block, named **Prediction accuracy**, evaluates the prediction error (based on a comparison between the actual speed profile evaluated by GPS and that estimated by the prediction system). The output of the Prediction accuracy block could be used to trigger a new prediction run.

3.1 Driving cycles

In the present investigation three kinds of driving cycles were taken into account to analyze the performance of intelligent plug-in vehicles. The first two are standard driving cycle adopted for the registration on new cars in Europe (NEDC and ECE).

Other cycles were obtained with the help of SUMO by simulating the traffic in the Ecotekne campus (Fig. 4) of the University of Salento for about 10000s (2.8h) and the center of Lecce (Fig. 5 and Fig. 6).

Fig. 4. Map of Ecotekne campus

Fig. 5. Map of Lecce used for the simulation with SUMO

Fig. 6. Snapshot of SUMO simulation showing the target vehicle (BEV)

The specification of the vehicles are used in the framework of SUMO to calculate the maximum values of acceleration/deceleration allowed to each vehicle according to the difference between the actual power request (depending on aerodynamics, rolling and inertia) and the maximum traction/braking power of the vehicle. Cycles obtained in this way were named as Trace A to Trace C. More details on the procedure used to obtain the numerical cycles can be found in [24].

Cycle	Total time [s]	Average speed [km/h]	Length [km]	Max speed [km/h]
Cycle_NEDC	1225	33.6	11	120.0
Cycle_ECE	205	18.7	1.01	50.0
Trace A	10001	16.9	46.94	50.0
Trace B	10801	24.8	74.33	50.0
Trace C	830	22.0	2.9	60.0
Cycle R*25	9550	25.7	68.3	41.6
Cycle Q	1916	14.84	8.19	55.0

Table 1- Driving cycles

Finally cycles R and Q were taken into account. These cycles were acquired on-board of a city car with a GPS system in the Ecotekne campus (Cycle R) and in the center of Lecce (Cycle Q). Cycle R has been assumed to be executed for 25 times (R*25) in order to obtain a duration comparable with those of cycles A and B.

The specifications of the cycles taken into account in the investigation are reported in Table 2. Note that all the cycles taken into account in the present investigation refer to a zero grade condition.

4 The PHEV case

ITAN500 is a four-wheel vehicle prototype with a size comparable with that of a large scooter. ITAN500 can be classified as PHEV40 because its all-electric range is 40 miles on the UDDS cycle. The vehicle was designed to reach a maximum speed of 90km/h in hybrid configuration with a mass of about 800 kg. By taking into account the overall transmission ratio (1/3.46) the DC motor was selected in order to generate a torque of about 27 Nm at the speed of 3560 rpm. A set of six lead acid batteries in series are used to produce the nominal voltage of 72V required to feed the electric motor. The choice of lead acid batteries was due to the need of reducing the vehicle cost. However, other kinds of batteries are currently under consideration.

A small gasoline engine with a maximum power of 9.9kW at 3600 rpm is used to extend the range of the vehicle. More details on the power-train (shown in Fig. 7) can be found in a previous publication ([24]).

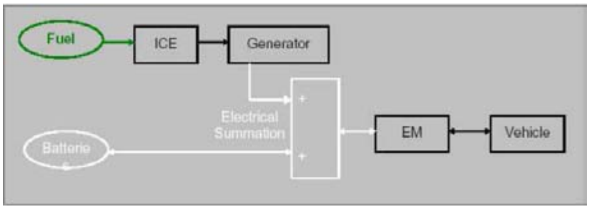

Fig. 7. Scheme of the ITAN500 power-train

The vehicle can be run in three different modes.

Mode 1: the power to the motor is supplied only by the generator/engine group;

Mode 2: only battery is used to supply power;

Mode 3: the engine is used both to charge battery and to supply power to the motor;

Mode 4: the engine and the battery are used together to feed the motor.
An adaptive heuristic control technique has been developed and presented in previous investigations. ([26]). The technique selects the operating mode of the powertrain (1-4) according to actual State of Charge and required engine power.
The thresholds used for engine power and SOC can be:

- Optimized for NEDC cycle and kept constant for each cycle (*no-knowledge* approach);
- Optimized for each cycle (*full-knowledge* approach);
- Optimized for mini-reference cycle similar to that predicted in the next time window (*prediction&maps*).

In each case, the goal of the optimization is the reduction of the equivalent fuel consumption calculated in the following way:

$$\dot{m}_{tot} = w_{FC}\dot{m}_{ICE}(\vartheta) + \dot{m}_{eq,BATT} \quad (1)$$

$\dot{m}_{tot} = w_{FC} * \dot{m}_{ICE}(\vartheta)$ where:

$\dot{m}_{ICE}(\vartheta)$ is the effective fuel consumption function of engine temperature θ;

w_{FC} is the weight assigned to the level of fuel stored in the tank. It is set equal to 1 if the tank level is greater than 25% When the tank level is very low, this parameter is increased to prefer battery usage when the fuel level is low. In particular w_{FC} is 1.2 for 10%<tank_level<25% and 1.5 for tank level lower than 10%.
Note that eq. (1) has been obtained by adapting the equivalent fuel consumption defined by Sciarretta et al. [8] for a parallel HEV to the specific power-train of ITAN500.

The equivalent fuel consumption of the battery is obtained as follows:

$$\dot{m}_{eq,BATT} = \frac{\eta^{\gamma} \cdot P_{BATT}}{Q_{LHV} \cdot \Delta t} \quad (2)$$

where η represents the average fuel consumption of the battery which is assumed to be constant and the same in charge and discharge in the present investigation.
When the battery is in charge, P_{BATT} represents the power that could be stored in the battery. Due to the battery efficiency η, the actual power stored in the battery (which define the equivalent fuel consumption) is lower than P_{BATT}. This is taken into account by setting γ=1. In discharge, P_{BATT} is the power requested from the battery is increased by η (γ=-1).
To complete the description of eq. (3), Q_{LHV} is the lower heating value of the fuel (in the present investigation gasoline is considered with Q_{LHV} =44MJ/kg while Δt is the time step of the driving cycle (Δt =1s).
The penalty function $f_p(SOC)$ takes into account the battery usage in the optimization process and has been defined according to Sciarretta et al. [8].
The results of the three approaches in terms of fuel consumption are shown in Fig. 8.

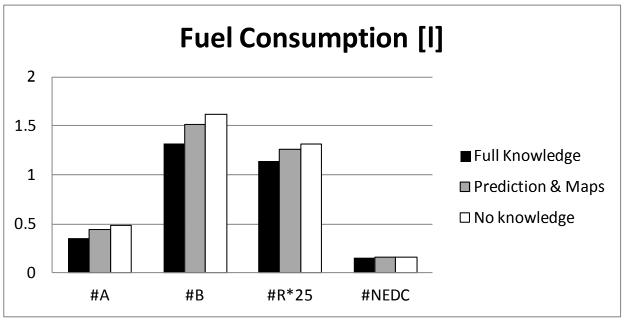

Fig. 8. Fuel consumption with the proposed approaches (initial SOC 75%)

Note that the complete knowledge of the future driving conditions would reduce fuel consumption from 13% (cycle #R*25) to 27% (cycle #A) with respect to no knowledge. The prediction & maps approach (more realistic) gives a reduction of about 8% of fuel consumption over the three cycles (#A, #B and #R*25) with the proposed heuristic technique.
To explain the results of Fig. 8, the corresponding SOC traces are shown in Fig. 9. The ideal SOC trace of a plug-in vehicle is also shown. It is represented by a linear decrease from the initial SOC to fully discharged battery (SOC=20%) exactly at the end of the mission (so-called *blended mode*).
The traces of SOC obtained with the proposed strategy show an initial zone where the results corresponding to *full knowledge*, *prediction&maps* and *no knowledge* are perfectly overlapped and the SOC decreases monotonically (Electric Mode) [25]. Of course this region is particularly evident and relevant when the initial SOC is higher (75%).
Then, there is a region in which the SOCs tends to decrease but can be kept locally constant or be increased thanks to the use of the engine (Plug-in Hybrid Mode). This region ends when the battery is fully discharged (SOC=20%). After this, the SOC remains globally constant for all cases (*full knowledge, prediction&maps* and *no knowledge*) with small variation that are not visible in the scale

used for the Fig. 9 (Discharged Battery Mode). Thus, the different results in terms of fuel consumption and CO_2 emissions obtained with the three methods can be accounted for with the different duration of the EM, PHM and DBM zones. In the EM region, the fuel consumption is zero but the SOC strongly decreases due to the extensive use of the battery. In the PHM mode, the battery is the main energy source and the engine is turned on (when its efficiency is high) to decrease the slope of the SOC trace. The DBM region is the worst in terms of fuel consumption because engine has to be run also in its low efficiency region since batteries are fully discharged. When the vehicle mission is entirely known (*full knowledge* case), the vehicle reaches the minimum SOC at the end of the mission even if it does not follow exactly the ideal case. The traces of Fig. 9 show that the proposed method performs better than the *no knowledge* case since it allows to reduce the length of the DBM and to increase the PHM. As a consequence, the ICE is averagely run at higher efficiency (Fig. 10) and for less time (Fig. 11).

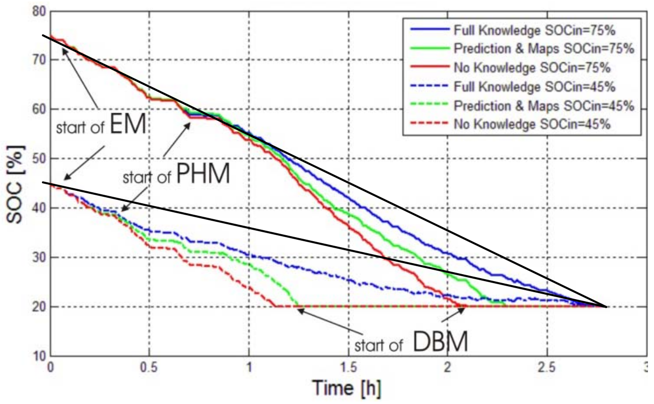

Fig. 9. SOC vs. time for Trace #A

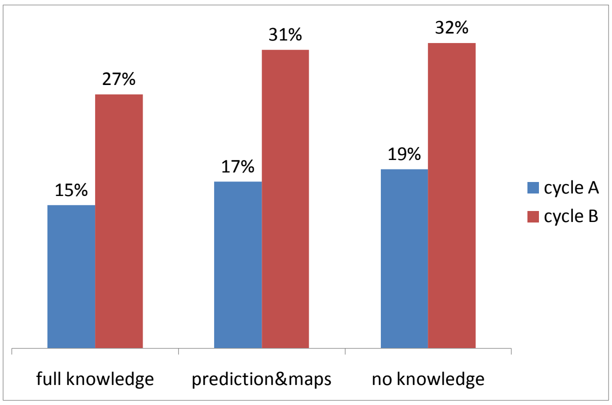

Fig. 10. Percentage of mission with engine ON for #A and #B (SOCin=45%)

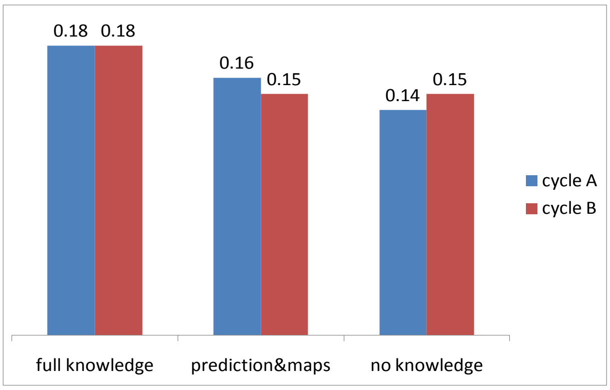

Fig. 11. Average efficiency of the engine (SOCin=45%)

4.1 CO_2 emissions

Emission from cars is one of the most important source of CO_2 concentration in urban centers [27]. From this point of view only tank-to-wheel emissions should be taken into account. However, the ultimate goal of advanced power-train technologies is to reduce the overall emissions of greenhouse gases. Thus, it could be interesting to evaluate the overall well-to-wheel (WTW) emissions of CO_2 produced with the different approaches considered in this investigation.
The complete combustion of 1 liter of gasoline produces 2.4 kg of CO_2. Assuming a density of 700 kg/m3, 1 kg of gasoline produces 3.42 kg of CO_2 (tank to wheel emissions). Sullivan et al. [28] consider a multiplying factor of 1.162 to pass from TTW to WTW emissions of CO_2. Thus, a kg of gasoline can be assumed to produce 3.98 kg of CO_2 (WTW). Using this conversion factor, the total CO_2 produced along the cycles #A, #B and #R25 has been calculated from the results in Table 3 (i.e. for the full knowledge case).
As for the electric path, the TTW contribute is obviously zero while the well-to-tank (WTT) emissions depend on the energy mixing used to generate the electricity stored in the batteries. A report from the International Energy Agency, [29] indicates for Italy an average emission of 0.386 kg of CO_2 per kWh of electric energy. Using the data about the capacity of the batteries (equivalent 1.8 kWh) and the results in terms of SOC, it is possible to evaluate the total energy used for each cycle and for each approach. Thus, the electric WTT emission of CO_2 can be easily calculated.
Note that in the framework of intelligent transport system, the actual CO_2 emission per kWh can be communicated to the vehicle from the recharging infrastructure. This could help the driver or the energy management strategy to avoid recharging the vehicle when this factor is particularly high.

The calculated values of CO_2 emissions from engine and batteries are reported in Fig. 12 and Fig. 13. Note that the electric emissions are almost negligible with respect to the quantity of CO_2 produced by the engine even if the engine is used only for a fraction of the mission. Moreover, they are the same for both approaches since batteries are fully discharged in both cases.
The results reveal that complete information about the future driving mission could help to significantly reduce the overall emission of CO_2 from a plug-in series HEV. The estimated reduction ranges from 12% for cycle #R*25 to 18% for cycle #A.

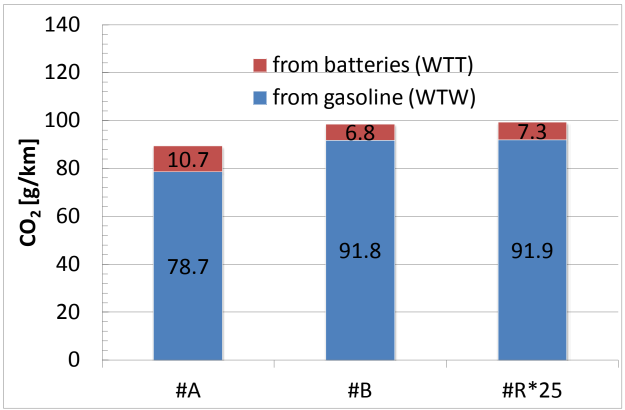

Fig. 12. Well to wheel emissions of CO_2 for the no-knowledge case

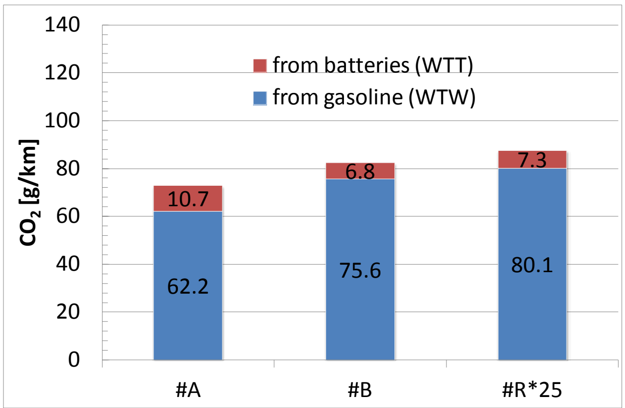

Fig. 13. Well to wheel emissions of CO_2 for the full-knowledge case

5 The BEV case

For the BEV case, the Smart ED vehicle has been taken into account compared with the traditional gasoline version (gasoline engine, 45kW).
To underline the effect of driving cycle specification on the range of an electric vehicle, both cars have been simulated with AVL-Cruise software using literature data ([30],[31]) for the vehicle components (Table 2).

	Unit	Smart gas. 45kW	Smart ED
Weight	kg	730	980
Range (EUDC)	km	-	97
Prime motor		3-cylinder gasoline engine (max torque 95Nm)	PM electric motor (max Torque125 Nm)
Secondary motor			Motor/inverter unit
Energy storage		Gasoline tank	Zebra batteries 50Ah, 26.6kW
Fuel cons.	liter/100km (NEDC)	4.7	-
Rated CO2 emissions	TTW g/km	113	-

Table 2 – Specification of Smart gas. and Smart ED

Fig. 14 and Fig. 15 show the speed profile and the corresponding discharge curve of the electric vehicle for cycle Q and cycle ECE repeated about 3 times to match the length of cycle Q (2.9km).

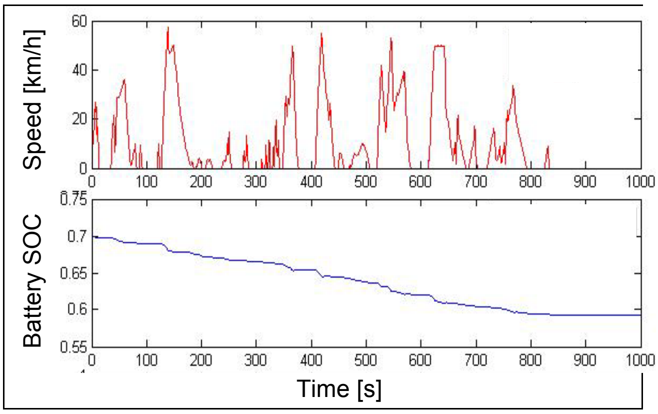

Fig. 14.Speed trace and battery SOC for trace C

The results shown that the energy necessary to execute a trip of 2.6 km strongly depends on the driving cycle that in turns depends on internal (vehicle status, driving styles) and external factors (weather, traffic conditions). A complete or partial knowledge of the future driving conditions can help the driver to have more accurate information about the actual range of the vehicle thus reducing range concern.

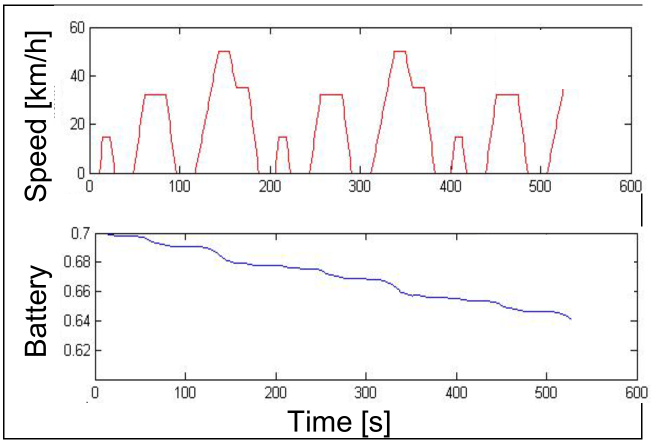

Fig. 15. Cycle trace and battery SOC for trace ECE (*no-knowledge approach)*

The results of the analysis on cycle ECE and Q are summed up in Table 4.

	Full knowledge	*No knowledge*
Final SOC	59%	63.5%
Equivalent gasoline consumption	2.9 liter	4.9 liter

Table 3 - Energy usage of BEV in the case of full knowledge and no knowledge

	Unit	**NEDC**	**A**	**B**	**R**	**Q**
Average speed	km/h	33.6	16.9	24.8	25.7	14.8
stops per km		1.1	1.2	0.4	0.4	2.8
avg positive acc	m/s^2	0.54	0.51	0.5	0.45	0.8
avg neg acc	m/s^2	-0.2	-0.9	-1.0	-0.5	-0.8
Smart ED range	**km**	**134**	**111**	**119**	**142**	**82**
Smart gas. mileage	**km/l**	**21.8**	**7.3**	**12.4**	**17.5**	**5.8**

Table 4 – Results of the simulation for Smart ED and Smart gasoline 45kW

The results of the investigation on the vehicles with respect to the other driving cycles of Table 1are shown in Table 4 together with cycles' specification in terms of average speed, acceleration and number of stops per km.

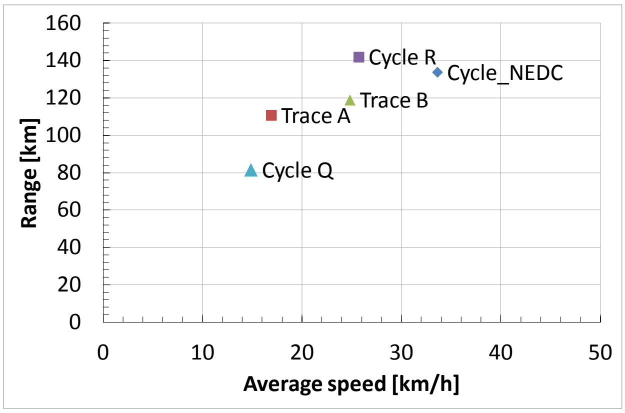

Fig. 16. Electric vehicle range vs. average speed

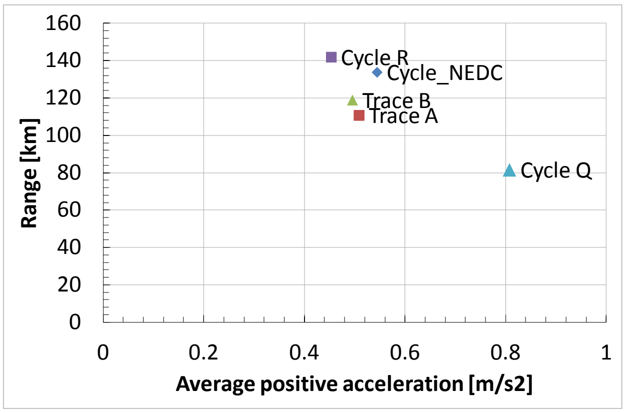

Fig. 17. Electric vehicle range vs. average positive acceleration

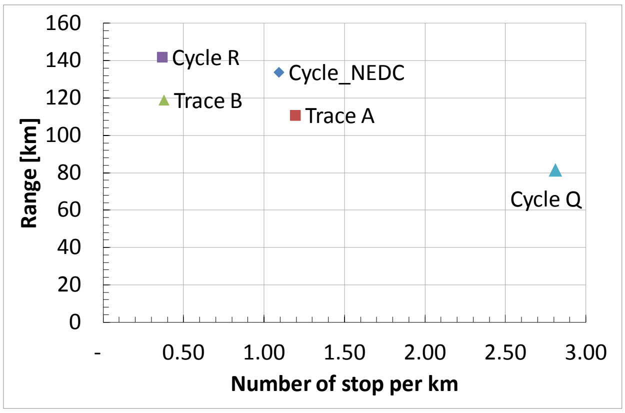

Fig. 18. Electric vehicle range vs. number of stops

Note that electric range tends to decrease when increasing the average positive acceleration (Fig. 17) or the number of stops (Fig. 18) and decreasing average speed (Fig. 16). No correlation has been found with the average negative acceleration.
The consumption of the conventional gasoline smart is more influenced by the driving cycle specification. Fig. 19 shows the correlation between the range of the electric vehicle and the fuel consumption of the conventional vehicle. Both

values have been made dimensionless by dividing for the corresponding average value.

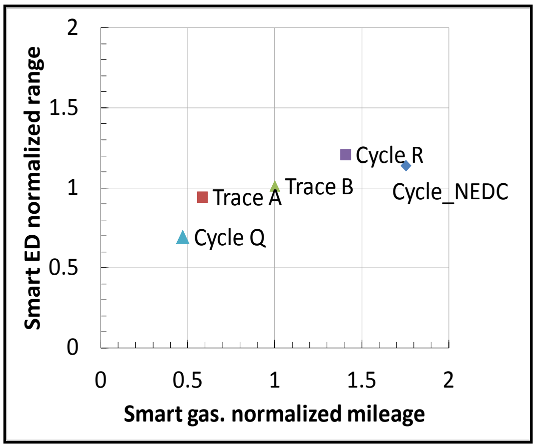

Fig. 19. Gasoline Smart mileage vs. Smart ED range

Note that gasoline vehicle is more affected by the specification of the driving cycles. This can be explained by taking into account that engines consume fuel also when the vehicle is stopped (queues, cross lights, etc) or braking. Moreover, the overall efficiency of a gasoline internal combustion engine strongly decreases when the engine is run at partial load while electric motor and batteries have an almost constant efficiency over the driving cycles.

5.1 Emissions of CO_2

The emissions of CO_2 were calculated for both the conventional and electric Smart with the Well-to-Wheel approach described for the hybrid case. (Fig. 20). Note that the electric vehicle produces very low emissions compared with the conventional gasoline. Moreover, they are less influenced by the driving cycle than that produced by the gasoline engine as a result of the poor efficiency at idle and partial loads.

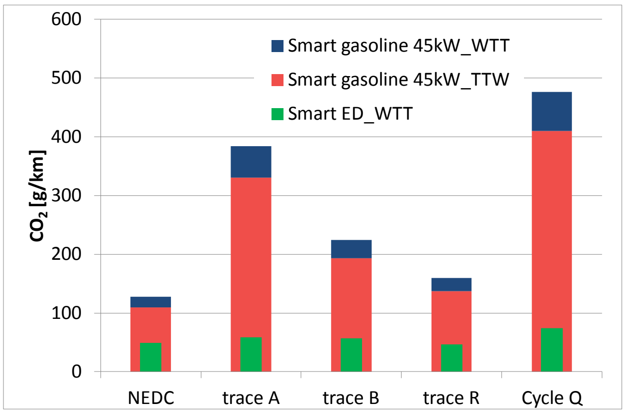

Fig. 20. WTW emission of the BEV compared with the conventional powertrain

6 Conclusions

The potentiality of ICT to improve the energy consumption of plug-in vehicles by giving information on internal and external driving conditions has been analyzed numerically with respect to a plug-in hybrid electric vehicle and a battery electric vehicle. In particular, the investigation focused on the possibility to predict the future power request demand and the corresponding effect on fuel consumption and Well-To-Wheel emissions of CO_2 for the Plug-in Hybrid Electric vehicles.

The results show that the knowledge of the driving cycle in a future time window can improve both fuel consumption and total CO_2 emissions in a series PHEV with Blended Mode control up to about 20%.

In the case of a battery electric vehicle, the proposed method can help the driver to have more accurate information about the actual range of the vehicle thus reducing range anxiety. The electric range and the CO_2 emissions of the Battery Electric Vehicle were found to be affected by average speed, average positive acceleration and number of stops.

5 List of acronyms

AEE	All Electric Range
BEV	Battery Electric Vehicles
CBD%	% of mission with controlled battery discharge
CD	Charge Depleting
CS	Charge Sustaining
ECMS	Equivalent Consumption Minimization Stategy
EngON%	% of mission with engine turned on
FCV	Fuel-Cell Vehicles
GPS	Global Positioning System
HEV	Hybrid Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicles
ICE	Internal Combustion Engine
SOC	State of Charge
TTW	Tank-to-Wheel
WTT	Well-to-Tank
WTW	Well-to-Wheel

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