Discovering Regions Where Users Drive Inefficiently on Regular Journeys

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***Abstract*—In this paper, we propose a mechanism to optimize fuel consumption on regular routes. The idea is to find out in which areas a driver usually realizes inefficient actions from the point of view of energy consumption. The aim is to alert the user in advance in order to adjust the vehicle speed or change gear, avoiding inefficient driving. Unlike other proposals, this solution does not require the driver to change the route in order to save fuel. To detect inefficient areas, the system uses vehicle telemetry: acceleration, deceleration, engine speed, engine load, and vehicle speed. A fuzzy logic system determines whether the driver drove efficiently or not in a region. Then, when the driver drives in the same route, the system predicts if the driver will return to a similar inefficient driving pattern in the nearby region. If the probability is high, the system warns the user. Therefore, the driver can take the appropriate action. The results show that the system reduces the fuel consumption by 7.33% on average and even, in certain cases, the fuel saving is more than 10%.**

***Index Terms*—Eco-driving, fuzzy logic, intelligent transport system, multilayer perceptron (MLP).**

I. Introduction

The TRANSPORT sector demands 33% of the total energy in Europe [1], [2]. The production of this energy is very expensive. Furthermore, not-efficiently used vehicles emit a large quantity of polluting gases into the atmosphere. These gases cause a large number of deaths [3]. In this context, governments have taken legal requirements for manufacturers to reduce emissions of CO_2 from all cars sold. Currently, emissions of nitrogen oxides (NOx), total hydrocarbon, nonmethane hydrocarbons, carbon monoxide (CO), and particulate matter are regulated for most vehicle types. Compliance is determined by running the engine at a standardized test cycle such as the New European Driving Cycle.

In recent years, manufacturers have reduced the vehicle weight and improved aerodynamics and engine technologies in order to save fuel. However, drivers could improve fuel consumption even if driving an old model of vehicles without these advances. They can minimize the demand for energy by changing their driving style to a more efficient one. This is known as eco-driving. Eco-driving is a driving technique based on the setting of the parameters that the user controls, such as vehicle speed, gear, and acceleration. This technique allows us to save fuel regardless of the technology [4], [5]. Applying eco-driving techniques, we can save a lot of fuel, although the exact amount depends on the skill of the driver, the vehicle type and the environment. In the related literature, there are many works that demonstrate the suitability of these techniques in order to minimize the fuel consumption and greenhouse gas emissions. In [6], the authors analyzed the influence of the driving style and the road characteristics in the emission of pollutant gases. Their conclusions were that eco-driving advice can save from 5% to 25% of fuel. Other proposals are based on partial theoretical models that calculate the optimal cruising speed for the vehicle [7], taking into account the engine characteristics and basic physics–dynamics rules. Some authors agree on the importance of anticipating the behavior of other vehicles in the traffic flow or the state of traffic lights. The authors in [8] propose the use of model predictive control of a vehicle in a varying road-traffic environment for ecological driving based on anticipation of the road and traffic in a crowded road network regulated by traffic signals. The authors in [9] proposed a system to provide real-time advice based on changing traffic and infrastructure conditions by adjusting the speed of the vehicle if the information of the timing in upcoming traffic lights is known. The potential impact of such systems, apart from requiring the deployment of an infrastructure to vehicle communication architecture, is only in the majority of simulated cases.

In addition to the energy saving, an eco-driving style has other advantages such as the following.

- Increasing the lifetime of the vehicle components: This driving style requires less work of the vehicle systems (brakes, clutch, gear box, engine, etc.) in comparison with a conventional driving style.
- Reducing the pollutant gas emissions: Greenhouse gases emissions are directly associated with the amount of fuel burned during the trip. Greenhouse gases are emitted when fossil fuels, such as coal, oil, and natural gas are burned in order to obtain energy. Therefore, less fuel consumption involves a reduction of pollution. One of the main measures taken by governments to comply with the agreements on emission of gaseous pollutants is to decrease the pollution caused by the transport sector.
- Decreasing the driver stress: Eco-driving requires a mental state of peace and calmness. The study in [10] realized a comparison between the fatigue experienced during

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normal driving and the fatigue caused by eco-driving. The simulated driving experiment was realized by a universal driving simulator system, and surface electromyography of the leg muscles of ten subjects was measured in order to clarify the physical fatigue of a driver in different driving modes. The conclusions showed that fuel economy in eco-driving with an eco-indicator is higher than other driving modes, and muscle activities are lowest by signal analysis of the surface electromyography. Authors also demonstrated that an eco-indicator is an effective assistant system to help a driver realize eco-driving, as well as to reduce the physical burden of the driver.
- Decreasing the risk and severity of traffic accidents: This driving technique is based mainly on foresight and anticipation. Therefore, the safety of the driver and passengers is improved.
- Improving the traffic flow: Using this driving technique, the driver accelerates more effectively and adjusts the vehicle speed, avoiding stops and maximizing the movement on coasting. As a result, it improves the average road speed.

Many authors propose that the driver changes route in order to save fuel. Such proposals are called eco-routing. In some cases, the optimal route from the point of view of energy consumption is not the route with the minimum time [11], [14]. Other parameters such as slope, speed limits, and traffic density or the number of stops can determine the best way to reach the destination. Eco-routing is based on a weighted graph representation of the road network, where the edge weights capture the environmental impact of traversing the edges. The weighted graph is employed to obtain the optimal route. This route is estimated using routing algorithms such as Dijkstra's algorithm, A^* algorithm, and Greedy algorithms.

In recent years, several authors have proposed to use social networks to improve driving and encourage drivers to drive efficiently. A method for utilizing fuel consumption data in an incentive system for the Tampere City Transport, based on sharing an individual driver's average fuel consumption in a specific group compared with the average fuel consumption of all drivers in that specific group, was proposed in [12]. A different social aware system to promote eco-driving was presented in [13]. The system used mobile and information and communication technologies to promote eco-driving and safe-driving. The information was made available through a web site and some social experiments for the promotion of eco-driving and safe-driving were implemented.

In [14], the authors proposed a social navigation system in order to provide the drivers with enough information to choose the optimal route. Current navigation systems can calculate the best route, taking into account real-time traffic flow data, as well as historic data to predict traffic flows. However, they are not able to determine the road conditions and the current reason and status causing the traffic jams. Information sharing between drivers allows us to improve safety and to save fuel. However, the vehicles' networks standards have to adapt to this type of applications. Safety and ecological applications require messages to arrive quickly and effectively and not to be lost. In [15], the authors proposed an algorithm to increase the system reliability in terms of probability of the successful reception of the packet and the delay of emergency messages in harsh vehicle environments.

On the other hand, there are journeys where the driver cannot change the route. Let us take, for example, a bus driver or a carrier. Other times, there is no alternative route to reach the destination. Regular journeys not only consume a big part of the energy consumed by a particular driver and emit a significant proportion of polluting gases but also a large number of traffic accidents happen on them, since the driver is distracted because the monotony of an already known road. We analyzed the vehicle telemetry obtained in previous work [16]–[18] and observed that drivers tend to behave always in the same way when they drive on regular routes, and they make mistakes (in terms of energy efficiency) in the same road sections. A good strategy to reduce the emission of pollutant gases is to optimize these trips that represent a very significant percentage of all journeys. In this paper, we focus on discovering road areas where the driver drives inefficiently in order to warn him or her and save fuel.

II. Discovering Regions Where Users Drive Inefficiently on Habitual Routes

The first step of the proposed algorithm is to find out in which regions the driver is driving inefficiently. Driving samples from the regular route are needed to perform this task. A fuzzy logic system evaluates the driver from the point-of-view of energy efficiency. The input variables are acceleration, deceleration, vehicle speed, engine load, and engine speed. The values are obtained from the on-board diagnostic port (OBD). Section III describes the OBD port more in depth. The output is a number between 0 and 10. A high score means that the user is driving efficiently. Moreover, we have to set a threshold to determine when a driver is efficient or inefficient. We consider that the driver is efficient when the score is equal to or greater than 5.

The solution evaluates the driver, taking into account the values of the input variables during a time interval. The time interval must be large enough not to penalize inefficient sporadic actions due to the environment, such as braking sharply once because a pedestrian is crossing. On the other hand, if the time period is too large, the system will become less accurate in the evaluation of the driver. In our tests, we set the time interval to 10 s. This value was obtained empirically, using the vehicle telemetry. Table I shows the success rate of driving evaluation compared with the assessments of experts distributed for highway, urban and conventional road, and taking into account the time interval. The median for each variable is calculated during this time interval. We use this statistical method because it is less sensitive to extreme values.

After performing a classification of samples as efficient or inefficient, in a second step, the EM algorithm (expectation—maximization algorithm) is used to cluster in K-warning areas the driving samples previously classified as inefficient taking into account the location (latitude and longitude). In addition, we should apply a filter in each k-warning area in order to remove it when the driving samples conclude that the driver

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TABLE I
TIME INTERVAL AND SUCCESS RATE OF DRIVING EVALUATION

Time Interval (Seconds)	Highway	Urban Road	Conventional Road
5	96.08%	88.77%	92.90%
10	96.21%	94.01%	93.80%
15	95.75%	92.5%	92.55%

was inefficient but the result was due to occasional situations such as a pedestrian crossing the street.

Finally, we build a prediction model in order to find out the driver behavior. This model is based on the vehicle telemetry samples and uses the multilayer perceptron (MLP) algorithm.

On the other hand, during the driving stage, the assistant employs the prediction model, location, and vehicle telemetry to determine if the driver is going to perform some inefficient action in a nearby area. Fig. 1 shows a schema of the proposed algorithm for optimizing usual routes.

III. Fuzzy Logic System for Driving Evaluation

A. Introduction

Fuzzy logic was introduced with the proposal of fuzzy set theory by Lotfi A. Zadeh [19] in 1965. He disagreed that only two options were permitted as belonging or not to a set (traditional binary sets). Unlike traditional logic, fuzzy logic defines degrees of truth and falsehood similar to human behavior; thus, it can manage specifications with vague information. This proposal has been applied to many fields, such as control theory artificial intelligence, image processing, and vehicular technology [20]–[22].

In fuzzy logic systems, each fuzzy set is characterized by a membership function that associates to each input a degree of belonging to the set. This function is continuous and can take values between 0 and 1. The transition between the two limits is gradually carried out unlike classic sets. Typically, membership functions are triangular, trapezoidal, or Gaussian due to its simplicity, although we could use any other. Fig. 2 shows the fuzzy logic model.

In summary, a fuzzy logic systems have the following components:

- Input Variables: They are needed to draw a conclusion.
- Membership functions: Assign to each of the input variables a degree of certainty of belonging to each of the fuzzy sets.
- Rules: Allow linking input fuzzy sets with output fuzzy sets through inference mechanisms.
- Defuzzification: Transforms the output fuzzy set to a numeric value.

B. Driving Evaluation

Fuzzy logic allows us to model the behavior of an efficient driver and to compare it with the driving style of the user. This type of logic is very useful because the concept of energy efficiency in the automobile field is imprecise since it depends on the vehicle, the environment conditions, and the priority of the trip. In a particular type of vehicle, acceleration intensities higher than 1.5 m/s^2 can mean an important increase in the fuel consumption, whereas in another car model, this value can be 2.0 m/s^2. As aforementioned, fuzzy logic structure consist of input variables, output variables, and rules. In our case, the inputs variables and the rules are based on the longitudinal dynamics of the vehicle given by

$$m_v \vec{a} = \vec{F}_t(t) - \left(\vec{F}_a(t) + \vec{F}_r(t) + \vec{F}_g(t)\right) \tag{1}$$

where $\vec{F}_t(t)$ is the traction force delivered by the car engine, m_v is the vehicle's mass, $\vec{F}_a(t)$ is the aerodynamic force, $\vec{F}_r(t)$ is the rolling force, $\vec{F}_g(t)$ is the gravity force, which is valid only if the vehicle is moving along a nonhorizontal road, and $\vec{a}$ is the vehicle's acceleration.

The engine-generated tractive effort is given by [13]

$$F_t = \frac{M_e \varepsilon_0 n_d}{r} \tag{2}$$

where F_t is the engine-generated tractive effort, M_e is the engine torque in newton meters, ε_0 is the overall gear reduction ratio, n_d is the mechanical efficiency of the driveline, and r is the radius of drive wheels in meters.

The aerodynamic force (3) depends on the speed and the vehicle shape

$$F_a = \frac{1}{16} C_x \times S \times v^2 \tag{3}$$

where C_x is the drag force, S is the vehicle's front surface (m^2), and v is the vehicle speed (in meters per second).

Rolling force can be calculated using

$$F_r = \mu \times P \tag{4}$$

where P is the vehicle mass (in kilograms), and μ is the rolling resistance coefficient (μ) whose value depends on a great number of parameters such as the surface, the radius of the tire, the weight, the tire pressure, the temperature, and the speed. However, we can estimate the coefficient using

$$\mu = \frac{k}{100}\left[5.1 + \frac{5.5 + 9p}{pn} + \frac{8.5 + 3p}{pn} * \left(\frac{x_2}{100}\right)^2\right] \tag{5}$$

where k is a coefficient dependent on the type of tire (0.8 for radial tires and 1 for diagonal tires), p is the weight per tire (t), pn is the tire pressure (in kilograms per squared centimeter), and x_2 is the vehicle speed (in kilometers per hour).

The gravity tends to avoid any body to ascend. It has a direct impact on the vehicle when we go up or down a slope because we have to overcome this force, which depends on the mass of the vehicle and the slope. When we go down, this force helps the movement, accelerating the vehicle. It is calculated using

$$F_g = P \times g \times \sin \propto \tag{6}$$

where P is the vehicle mass (in kilograms), g is the gravitational constant, and $\propto$ is the road slope angle.

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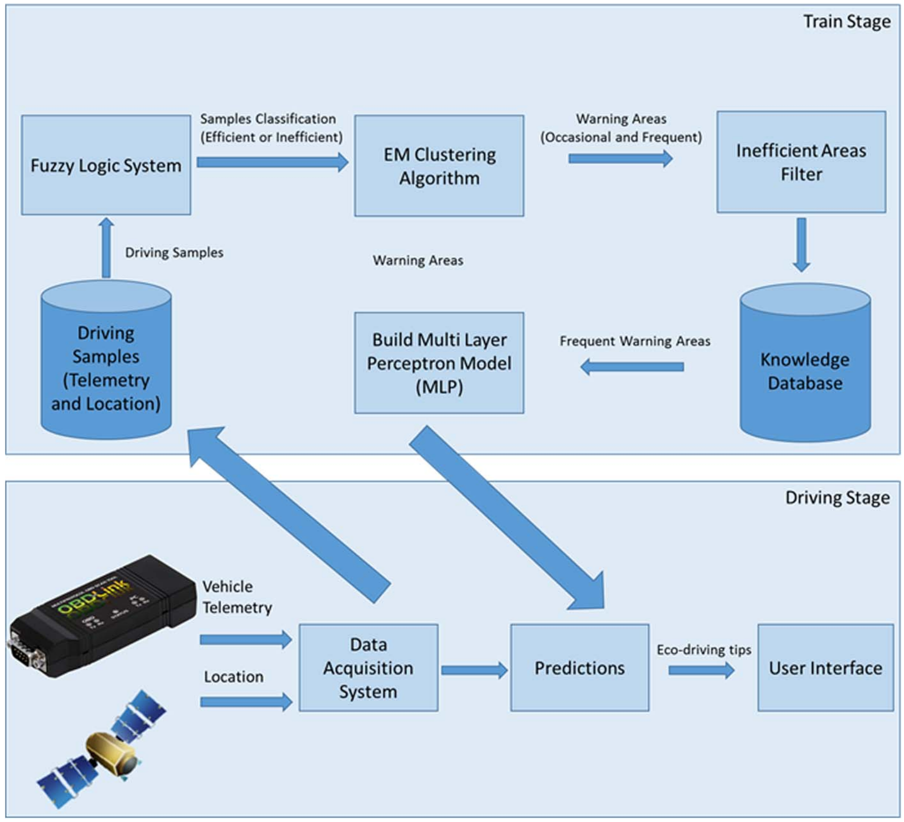

Fig. 1. Algorithm for optimizing usual routes.

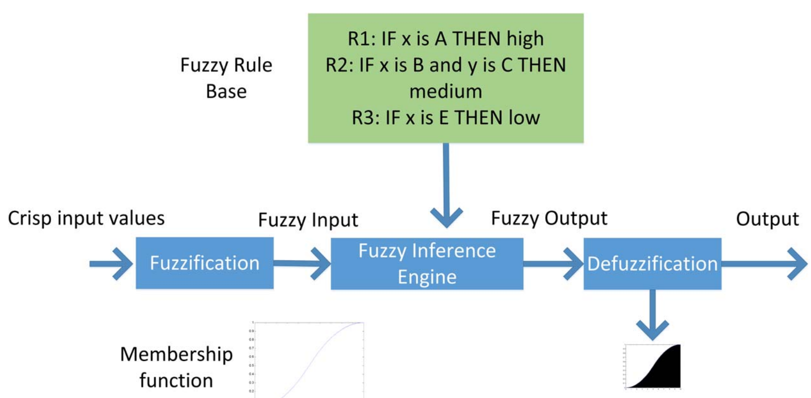

Fig. 2. Fuzzy Logic Model.

The input variables from the fuzzy logic system are the following:

- Acceleration: Fuel consumption increases exponentially when the driver accelerates sharply because it required more traction force as we can see in the longitudinal vehicle dynamic model (1). Traction force is provided by the vehicle engine when the fuel is burned. Therefore, more traction force involves that fuel consumption increases. In addition, on many occasions, there is no time to burn all the fuel released when the accelerator pedal is pressed down; thus, it is wasted. An efficient driver should avoid accelerating sharply in most of the route except in some situations. Sometimes, it may be necessary for safety reasons or because the fuel saving is greater. For example, if a traffic light is going to turn red, stopping and starting the movement of the vehicle will have an impact on fuel consumption that may be greater than using a sharp acceleration when the traffic light is still moving from green to red. Table II captures the median value of fuel consumption obtained with a Citroen XSARA Picasso 1.6 HDI when grouping the acceleration intensities in intervals. This table shows that the fuel consumption grows when increasing the acceleration intensity.
- Deceleration: when the driver brakes, previously generated energy is wasted because we have to provide a force equal to the traction force $(\vec{F_t}(t))$ calculated in (1) but in opposite direction. This force transforms kinetic energy into heat energy. The best method to stop is by using the "engine brake" without using the service brakes. The

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TABLE II
MEDIAN VALUE OF FUEL CONSUMPTION WHEN ACCELERATING

Acceleration (m/s^2)	Fuel consumption (l/100 km)
0.5 - 1	5.78
1 - 1.5	6.03
1.5 - 2	6.13
2 - 2.5	7.08
2.5 - 3	7.54
>3	8.17

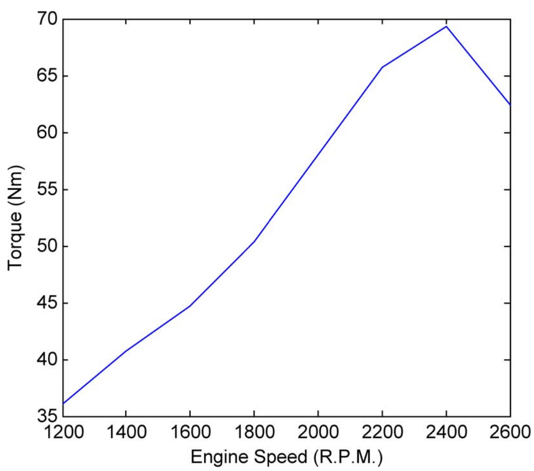

Fig. 3. Torque curve at partial engine load from Opel Insignia CDTI 2000.

objective is that the vehicle takes advantage of the kinetic energy to move until the point where the vehicle should stop or reduce the speed. In this case, the engine resistance causes a progressive reduction of the vehicle speed. The problem is that the OBD port does not allow us to know if the driver is using the brake pedal. Instead, we assess the intensity of the slowdown. If the intensity is high it means that the driver is making use of the brake pedal, otherwise the driver is assumed to be applying the "engine brake".

- Engine speed (in revolutions per minute) and engine load (in percent): Reducing tractive force (1) is not the only way to minimize the fuel consumption. We can optimize the power train changing gears to operate at best efficiency points. The power generated by the engine is proportional to torque and engine speed (7)

$$P = Mw \tag{7}$$

where P is the power (in watts), M is torque (in newton meters), and w is the angular velocity (in radians per second). The torque supplied by the engine has its maximum at an intermediate engine speed. When the engine speed exceeds a threshold, the torque decreases, and therefore, the power is lower. Fig. 3 captures the torque curve at partial loads of an Opel Insignia CDTI 2000. The horizontal axis is the engine speed (in revolutions per minute), and the vertical axis is the torque (in newton meters) that the engine is capable of providing at that speed. Fig. 4 shows the power curve.

The characteristic curves from the engine are used in order to know the performance in any condition of engine

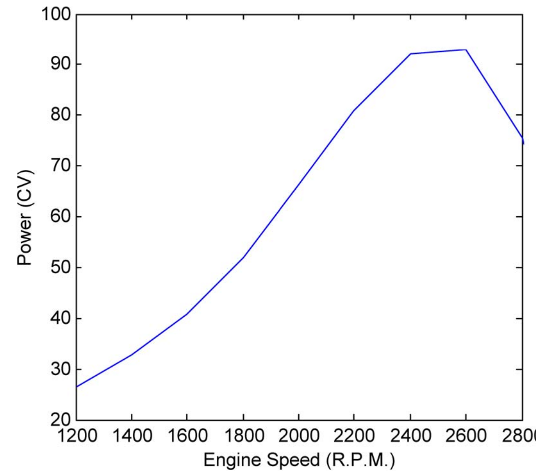

Fig. 4. Power curve at partial engine load from Opel Insignia CDTI 2000.

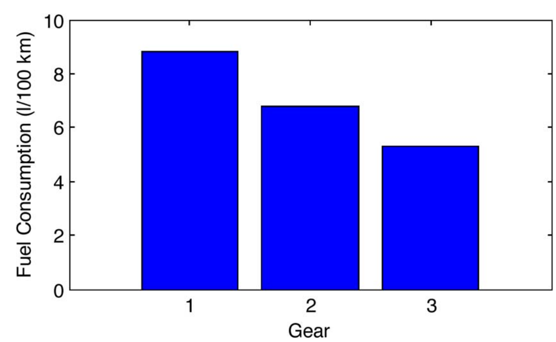

Fig. 5. Median values of fuel consumption at 60 Km/h with different gears.

speed and throttle position. Observing these curves, we can see that the maximum throughput is achieved when torque is about 90% and the engine speed is not high. This is accomplished when we drive at high gear. Fig. 5 captures the median fuel consumption obtained with different gears and at the same speed (60 Km/h). The vehicle employed for testing was a Citroen XSARA Picasso 1.6 HDI (Diesel). This figure shows that we should always drive at high gears when it is possible. If the current gear is high and the engine speed is too low, fuel consumption increases because the ECU (engine control unit) has to inject fuel in order to avoid that the engine stops. Moreover, driving at high engine speeds can have negative effects on the control of the vehicle.

- Vehicle Speed: It is a factor that influences energy consumption, although in recent years its impact has been reduced due to the improvements in aerodynamics and to the decrease in the vehicle weight. However, we must bear in mind that the drag force $\vec{F}_a(t)$ is a quadratic equation depending on the vehicle speed (3). Therefore, when the vehicle speed is very high, the fuel consumption can grow significantly. On the other hand, when the driver is driving at a high speed, the probability that he or she has to stop using the brake pedal is increased. Every time a driver uses the pedal, forward-movement energy is converted to heat by the brake pads and is lost.

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Another component of this type of systems is the set of rules. The set of fuzzy rules tries to build the behavior model from an efficient driver. The set of fuzzy logic rules we use consists of the following ones:

- *IF acceleration IS (soft or hard) AND deceleration IS soft THEN score is efficient*: Every time a driver uses the brakes, energy is wasted. On the other hand, when the driver speeds up, extra energy is required in order to increase the speed due to the acceleration resistance. Therefore, if the accelerations (positive and negative) are low and infrequent, the fuel consumption will also remain low. We should also highlight that if the driver accelerates sharply, and then, he does not slow down, the required energy is being employed efficiently.
- *IF acceleration IS hard AND deceleration IS hardt THEN score is inefficient*: Fuel consumption grows when the driver accelerates and brakes with frequency and intensity. In addition, it increases the wear on wheels and brakes. An efficient driver minimizes acceleration intensities (positive and negative) in comparison with aggressive drivers.
- *IF engine speed IS high and engine load is (low or high) and vehicle speed IS (low or normal) THEN score IS inefficient*: In this case, the engine is not in the optimal working region. This means the number of fuel grams required to produce a given amount of energy could be reduced by shifting gears and adjusting the throttle pedal position.
- *IF engineSpeed IS low and engine load is normal THEN score IS efficient*: Optimal engine performance is achieved when the engine speed is low and the accelerator pedal is pressed 3/4 parts. Under these conditions, the amount of fuel required to produce a certain amount of energy is minimal.
- *IF vehicle speed IS high THEN score IS inefficient*: Fuel consumption increases exponentially above a speed threshold. This threshold depends on the vehicle. Modern vehicles have improved the aerodynamics. Therefore, drivers can drive at high speeds and fuel consumption will not grow significantly. The speed threshold employed in the tests is about 110 Km/h. The increase in fuel consumption at this speed was important for the vehicles used in the experiments.

Figs. 6–9 capture the fuzzy membership function for each input variable. The membership function is the same both for negative and positive accelerations.

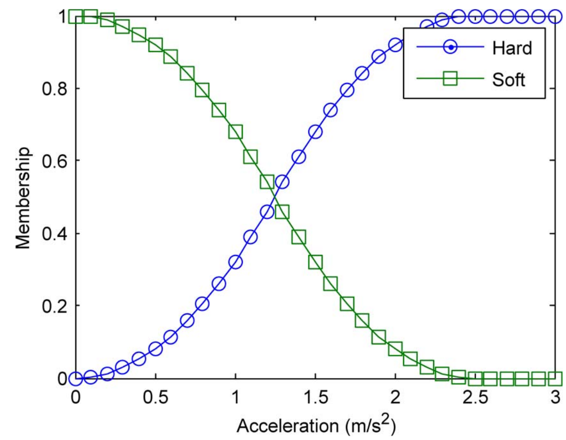

Fig. 6. Acceleration membership function (positive and negative).

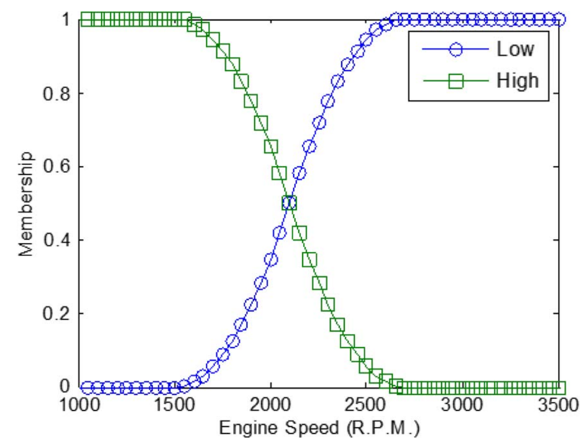

Fig. 7. Engine speed membership function.

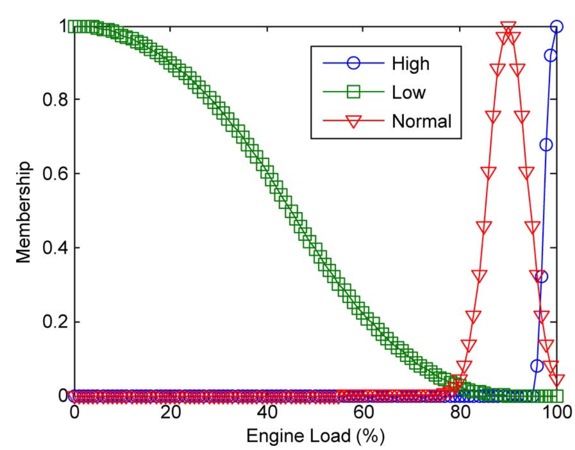

Fig. 8. Engine load membership function.

IV. EM Algorithm

A. Introduction

The EM algorithm was explained in 1977 by Dempster *et al.* [23]. This method had been proposed many times in special circumstances by other authors [24], [25]. However, they generalized the method and sketched a convergence analysis for a wider class of problems. A brief history of the EM algorithm can be found in [26]. This solution is applied in many scenarios, but particularly in image and signal processing. For example, [27] uses the EM algorithm to the problem of sequence detection when symbol timing information is not present. [28] introduces the algorithm for image restoration (deconvolution) based on a penalized likelihood formulated in the wavelet domain.

This probabilistic clustering algorithm is based on obtaining the probability density function to which data belongs. For estimating the probability density function, we can use a distribution such as Normal, t-Student, Bernoulli, Poisson, and log-normal. The distribution parameters are calculated maximizing

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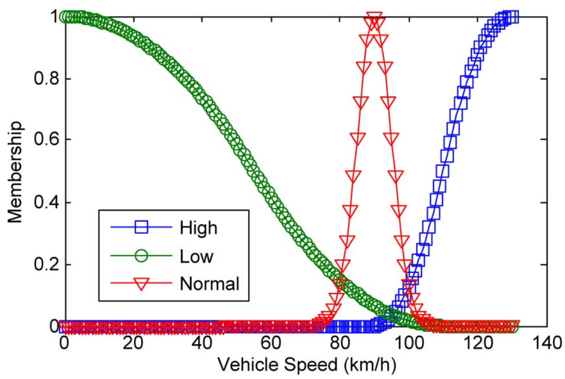

Fig. 9. Speed membership function.

the log-likelihood function. This function evaluates to what degree the data fit to the distribution function. In summary, the algorithm performs the following steps:

1) Initialize k Distribution Parameters $(\theta_1, \ldots, \theta_k)$: Each distribution parameter corresponds to a cluster. The number of clusters can be assigned manually or by using cross validation.

2) Expectation Step: Calculate the expected value of the log-likelihood function, with respect to the conditional distribution (1) of Y given X under the current estimate of the parameters θ^t

$$Q(\theta|\theta^t) = E_{Y|X\theta^t}\left[\log L(\theta; X, Y)\right]. \tag{8}$$

Each driver is assigned to a cluster using the parameters obtained in the initial stage or in the maximization step. Every instance is composed of an attribute vector. The attributes used to cluster the drivers have been previously described. The relevance degree of the points of each cluster is given by the likelihood of each element attribute in comparison with the attributes of the other elements of the cluster.

3) Maximization Step: It recalculates the parameters of distributions maximizing the log-likelihood function (2)

$$\theta^{(t+1)} = \arg\ \max\ Q(\theta|\theta^t). \tag{9}$$

4) Repeat Steps 2 and 3 Until the Number of Iterations Exceeds a Limit or Converge: This algorithm is useful for several reasons: conceptual simplicity, ease of implementation, and the fact that each iteration improves. The rate of convergence on the first few steps is typically quite good but can become slow when it approach a local solution. EM works best when the fraction of missing information is small and the dimensionality of the data is not too large. The main disadvantages are it can require many iterations, and E-Step can be very slow when the data have high dimensionality.

B. Discovering Inefficient Regions

Driving samples were classified into efficient or inefficient in the previous step (fuzzy logic system). Now, we have to group them by location, since it is possible that there are many nearby points. The idea is to split the route into areas. The warning assistant predicts if the user will drive inefficient when approaching an area. EM algorithm is used in order to group the labeled driving samples on regions.

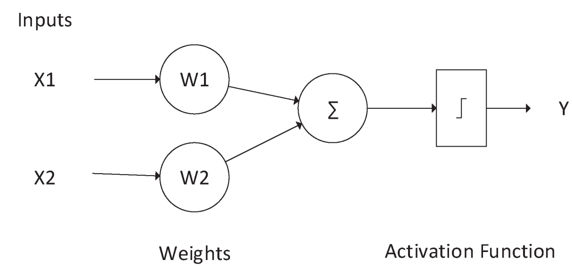

Fig. 10. Perceptron model.

In addition, we should apply a filter in each k-warning area in order to remove it when the driving samples conclude that the driver was inefficient but the result was due to occasional situations such as a pedestrian crossing the street. The filter consists of removing the regions, where the percentage of times that the driver drove inefficiently does not exceed a threshold. A high threshold means that some regions where the user behaves badly, from the point of view of energy, are discarded. However, a low threshold may cause the system to make inaccurate predictions about the driver behavior. In our case, the filter removes regions when inefficient driving samples are less than 20%.

V. MLP

A. Introduction

An MLP [29] and the vehicle telemetry obtained in real time are employed in order to predict the driver behavior. This algorithm is an artificial neural network that has multiple layers and whose main advantage is to allow nonlinearly separable problems. This type of algorithms can be generalized. We can classify an element based on other elements that have been previously classified and which have the same characteristics.

Neural networks were proposed in 1940, when Warren McCulloch (a psychiatrist and neuroanatomist) and Walter Pitts (a mathematician) explored the computational capabilities of networks made of very simple neurons [30].

Later, in 1943, [31] introduced the perceptron (Fig. 10), the simplest form of a neural network. The perceptron consists of a single neuron with adjustable synaptic weights and a threshold activation function. This proposal guaranteed the convergence only if the problem was linearly separable due to the basic properties of the perceptron, which separates entries into two outputs.

An MLP overcome many of limitations of single-layer perceptron. However, there were no effective training algorithms. This problem was solved by [29]. They called the method "backward propagation", and it is based on least means square algorithm (LMS) [32].

The basic MLP structure consists of an input layer, output layer and one or more hidden layers. The number of layers determines the kind of problem that we can solve. The single-layer perceptron is limited to calculating a single line of separation between classes. On the other hand, a three-layer perceptron can produce arbitrarily shaped decision regions. The single-layer perceptron is limited to calculating a single line of separation between classes. On the other hand, a

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three-layer perceptron can produce arbitrarily shaped decision regions (Kolmogorov theorem) and are capable of separating any classes. Each layer has a set of neurons. The number of neurons depends on the type of problem to be solved. The neurons are connected with other neurons using weighted connections.

The MLP has the following steps:

- Initialization of weights and bias. Usually it is randomly done.
- Calculate the output of all neurons of the neuronal network according to (10). The output value of a neuron in layer n is part of the input value from neurons in layer $\mathrm{n}+1$

$$y = \sum_i w_i x_i - \theta \tag{10}$$

  where w_i is the synaptic weight of the connection, x_i is the input value, andθ is a bias term that regulates the degree of an activation to induce firing.
- The third step is to calculate the error in order to minimize it. The training stage on this type of algorithms is supervised. It defines a set of pairs (Xi, Yi) training patterns and an error function (11) (difference between the desired output and the value obtained). Once retrieved the error, the connection weights are updated (12) to minimize them

$$E_r = \sum_{p=1}^{p} E_p = \frac{1}{2} \sum_{p=1}^{p} (d_p - O_s^p)^2 \tag{11}$$

  where E_r is the total output error, E_p is the output error from neuron p, P is the number of neurons from the last layer, O_s^p is the output value from neuron p on layer s, and d_p is the expected output

$$w_{ij}^L(k+1) = w_{ij}^L(k) - \mu \frac{dE_T}{dw_{ij}^L} \tag{12}$$

  where w_{ij}^L is the connection weight between neuron i and j in layer L, E_T is the total error, k is the current iteration, and μ is the learning factor.

The algorithm can be improved by introducing a momentum term focused on accelerating the process, changing the size of the neuronal network or initializing the weight connections in a nonrandom way.

B. Prediction of Driver Behavior

The objective of the MLP is to predict the behavior of the driver in the inefficient area based on their prior behavior. The training data set has the following attributes:

Median value of vehicle speed: It is a factor that influences significantly on driving. High speed before reaching the inefficient region may mean that driver has to brake sharply in the inefficient area, wasting energy. On the other hand, as aforementioned in Section III, when the speed is high, fuel consumption increases because the aerodynamic force grows in quadratic proportion to the speed. However, modern vehicles have introduced aerodynamic improvements, minimizing the effect of the vehicle speed on fuel consumption as long as he or she does not have to brake.

Median value of accelerations: An unusually high value of acceleration near the inefficient region may indicate that the user is driving aggressively, and most probably driver will make mistakes in the inefficient region.

Median value of decelerations: The absence of slowdowns can predict a sharp slowdown at the inefficient region in order to adjust the vehicle speed. Sudden downturns have a negative effect on fuel consumption because the energy is wasted as heat.

Number of accelerations: In the case that the driver has speeded up very often before reaching the inefficient region is likely to have to brake later, arriving at the inefficient region. This sharp slowdown is due to the vehicle speed is very high.

Number of decelerations: If the driver performs corrections in the vehicle speed before reaching the inefficient region, it is possible to get avoid slowing down sharply in the inefficient area.

Traffic Density: The traffic state is one of the factors that determines the optimal speed along with topology and the road. If the traffic is heavy and the vehicle speed is high, the driver may be forced to slow down abruptly in the inefficient area.

Stop time: This variable can be used to find out the traffic state or if the driver will have to stop due to traffic lights or traffic signs, since they are synchronized following a specific pattern in many cities.

Positive Kinetic Energy (PKE): This variable measures the aggressiveness of driving and depends on the frequency and intensity of positive accelerations. A low value means that the driver is not aggressive. An unusual high value (close to inefficient area) may indicate that driver is going to continue driving inefficiently in the warning region. PKE is calculated using the following equation:

$$\mathrm{PKE} = \frac{\sum (v_i - v_{i-1})^2}{d} \tag{13}$$

where v_i is the vehicle speed (in meters per second), and d is the trip distance (in meters).

Median value of engine speed: This variable has a direct impact on fuel consumption, since it depends on the amount of burnt fuel and gear. An uncommon value can mean that the driver has to change gear when he or she arrives at the inefficient region. For example, if the engine speed is 2500 r/min near inefficient area, it is likely that the rotational engine speed will be 3000 r/min when vehicle reaches the warning region. In this case, the driver should change the gear in order to avoid an increase in fuel consumption due to the engine is not working at its optimum region. Torque decreases when the engine speed exceeds limit. The threshold depends on the engine and can be estimated with the torque curve.

Median value of engine load: Vehicle diagnostic port (OBD2) does not provide information about the position of the accelerator pedal. However, we can approach it through the engine load. In that case, its value can be obtained from the diagnostic port. When the engine load is low, it means that driver is not pressing hard on the brake pedal. Otherwise, a high value indicates that the throttle pedal is pressed fully. If the engine

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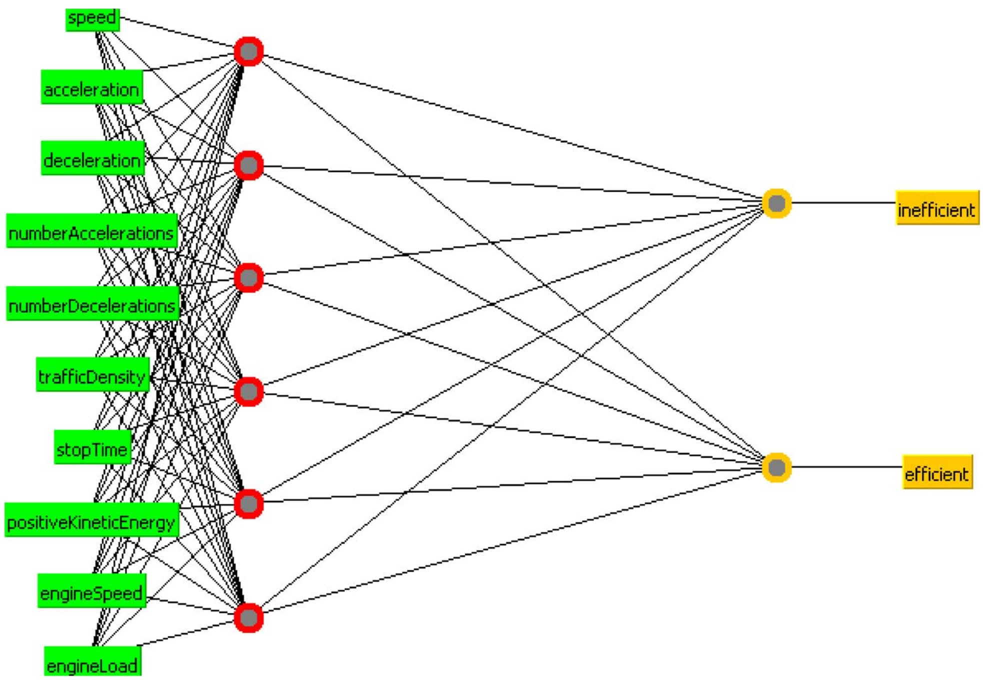

Fig. 11. MLP for the prediction of driver behavior.

load and engine speed are abnormally high close to the warning area, the driver will have to shift gears to save fuel.

The data set is built by calculating the median for each attribute during a time interval. We use this measure because it is less sensitive to outliers.

The architecture of the MLP is 10 (input layer) $\times$ 6 (hidden layer) $\times$ 2 (output layer). This architecture was obtained by performing many tests. Fig. 11 shown the MLP structure.

VI. Android Applications

The proposed system is implemented using an Android mobile device. These devices are ideal for obtaining information about the environment and the driving conditions due to their multiple connections (WIFI, 3G, and Bluetooth) and sensors (GPS). However, the proposed architecture and algorithms are flexible to be implemented using other types of devices.

The solution needs to obtain telemetry data from the vehicle in order to detect inefficient regions and predict the driver behavior. Telemetry is got from OBD. OBD port [33] was proposed in 1984 and it is known as the standard OBDI. OBDI has a strong mind focused on the assessment of the emission of gaseous pollutants from the vehicle. In 1988, OBD was improved and it was named as OBD2. OBD2 is an improvement over OBDI in both capability and standardization. This new version allows us to identify vehicle problems. In addition, we can monitor variables, such as speed, engine load, engine speed, mass air flow, etc. Vehicle manufactures have been required to install on-board diagnostic systems since 1996.

To obtain the vehicle diagnostic values, we connected a Bluetooth adapter [34] to the OBDII port. The mobile device sends a PID to a Bluetooth adapter. PID is an identifier. For example, the vehicle speed is obtained using PID “0D”. The

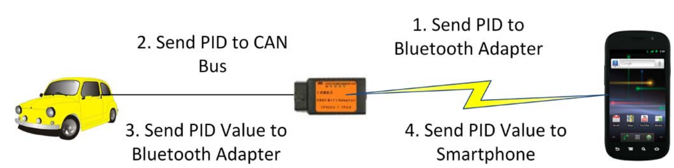

Fig. 12. Obtaining the vehicle telemetry from OBD.

Bluetooth adapter sends the PID to the vehicle’s bus. Then, a device on the bus recognizes the PID and sends the value for that PID to the bus. Finally, the Bluetooth adapter reads the response, and sends it to the mobile device. Fig. 12 shows the process to obtain telemetry data.

Our Android app uses the Torque plugin [35] to capture the vehicle telemetry from the diagnostic port. This plugin has the ability to pull information from all the accessible/available sensors in an ECU.

On the other hand, the EM algorithm and MLP have been implemented using an adaptation of Weka for Android [36]. The runtime-required resources are not significant because the algorithms are run only once, when the trip finishes.

Finally, the communication interface from the warning system is very important. Distractions due to the manipulation of devices, such as GPS receivers or mobile phones, are the cause of a large number of accidents [37]. When designing an in-vehicle information system it is important to ensure that the recommendations and the method to convey these tips do not negatively affect cognitive processing and driving performance [38]. The eco-driving assistant has to be as less intrusive as possible. Instructions using voice output are less distracting and more usable than those systems presenting the information on a visual display [39]. However, an accurate speech recognizer and a clear voice user interface are necessary [38].

Our Android app (warning assistant) uses vibration patterns to provide advice to the user. In our case, the assistant alerts

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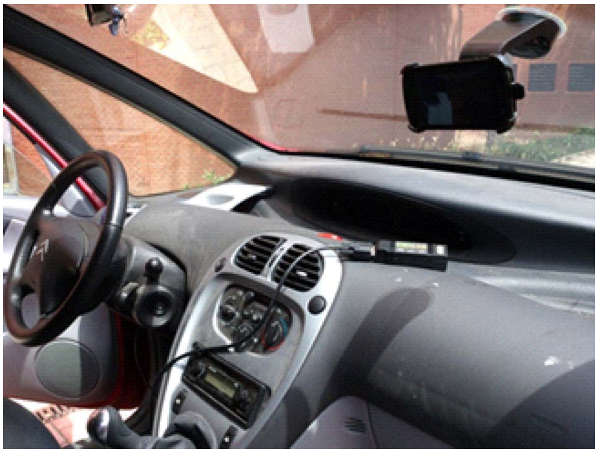

Fig. 13. Experimental setting.

the user with a long vibration pattern when the driver has to shift gears in order to avoid driving at a high engine speed. On the other hand, a short vibration pattern is used when the driver must slow down to minimize negative acceleration intensities.

In addition, the user can configure the assistant to replace the vibration notifications by a voice output such as "Release throttle" or "Shift gears" depending on the prediction or sound notifications. However, we have to take into account that during the conducted tests, some users said that the sound notification could be confused with an incoming phone call. Other users indicated that a voice locution could cause distractions. For this reason, the two options are offered, so that each user is able to select the most convenient one according to his or her preferences.

VII. Experimental Evaluation

Here the proposed prediction algorithm is validated and the fuel saving is also analyzed when using the system. The solution was deployed on a Galaxy Nexus [40] mobile device equipped with an ArmV9 processor at 1.2 GHz, 1 GB of RAM and Android 4.1.2. The OBDLink OBD Interface Unit from ScanTool.Net [34] was used to get the relevant data from the internal vehicle's CAN bus. The OBDLink OBD Interface Unit contains the STN1110 chip that provides an acceptable sample frequency for the system. In our tests, we obtain two samples per second. Fig. 13 shows an overview of the experimental setting.

Table III captures some related details for the drivers and the vehicles in the experiment. Tests were made at 8:30 A.M. in three different regions of Spain: Madrid, Seville, and Granada. Table IV captures the trip distance and the road type (expressed as percentage) for each route.

TABLE III
DRIVERS

Driver	Age	Experience (Years)	Vehicle
A	36	18	Citroën Xsara Picasso 1.6 HDI
B	38	15	Citroën Xsara Picasso 1.6 HDI
C	60	40	Citroën Xsara Picasso 2.0 HDI
D	55	35	Ford Fusion 1.4 HDI
E	60	41	Ford Focus Sedan 1.6
F	42	14	Citroën C5 2.0

TABLE IV
ROUTES

Route	Trip Distance	Highway	Normal Road	Urban Road	Region
A	8.3 Km	55.55 %	22.47 %	21.97%	Madrid
B	9.1 Km	49.54 %	16.48%	32.97%	Granada
C	10.5 Km	34.22 %	16.15%	18.07%	Sevilla

TABLE V
PREDICTION ALGORITHM

Region	Kappa Statistic	Correctly Classified Instances (%)	Incorrectly Classified Instances (%)
1	0.88	95.31	4.69
2	0.66	88.71	11.29
3	0.64	87.88	12.12
4	0.84	93.94	6.06
5	0.84	94.34	5.66
6	0.89	96	4
7	0.79	92.98	7.02
8	0.84	93.55	6.45
9	0.79	93.06	6.94
10	0.83	92.3	7.70

A. Prediction Algorithm

Table V presents the results considering the six drivers and were obtained using tenfold cross validation. The algorithm was trained with the telemetries got from drivers. The time frame was 10 s. This means that the drivers were evaluated every 10 s using the previously described fuzzy logic system. The neural network structure consisted of a single hidden layer with six neurons. The algorithm was run with the following parameters:

- Learning rate: 0.5.
- Momentum: 0.2.
- Epochs: 500.
- Prediction Distance: 130 meters.

The proposal is able to predict if the driver will perform inefficient actions by 92.81% on average. The average Kappa score from the proposed algorithm was around 0.63–0.89. This value indicates that the accuracy of this solution is good according to [41].

Table VI shows the results (success rate of the predictions) considering different classification models: MLP, Naïve Bayes and J48. J48 is the Weka implementation of the C4.5 algorithm [36]. Naïve Bayes and J48 were run with the default parameters from Weka. We can observe how the MLP algorithm gets the highest success rate in all cases. However, the J48 algorithm achieves a similar rate. The Naïve Bayes algorithm obtains the worst results. On the other hand, the execution times were 30 s

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TABLE VI
MODELS' COMPARISON TO PREDICT THE DRIVER BEHAVIOR

Region	MLP	Naïve Bayes	J48
1	95.31%	91.61%	94.86%
2	88.71%	85.45%	88.34%
3	87.88%	84.36%	87.87%
4	93.94%	93.83%	93.72%
5	94.34%	91.90%	93.46%
6	96.00%	95.45%	95.14%
7	92.98%	89.50%	92.31%
8	93.55%	89.79%	92.93%
9	93.06%	91.95%	92.46%
10	92.30%	88.73%	92.02%

TABLE VII
T-TEST FOR DRIVER A

	Assistant Disabled	Assistant Enabled
Mean	6.78 l/100 km	5.94 l/100 km
Variance	0.07	0.19
Observations	20	20
df	31	
T Stat	7.46	
P (T<=t) two tail	2.08E-08	

(MLP), 6 s (J48), and 0.2 s (Naïve Bayes). As conclusion, J48 algorithm could be a good solution in order to predict the driver behavior. Nonetheless, we have decided to use an MLP because the success percentage is slightly higher, and the execution time is not important, since the algorithm is executed only once, when the trip finishes. In addition, we may use cloud computing to reduce the execution time.

On the other hand, we could improve the accuracy of the algorithm and the prediction distance obtaining information about the environment such as traffic signs, weather conditions, traffic conditions, and telemetry from other vehicles. However, we would have to add sensors to the vehicle and to build a vehicular network. This solution will be more expensive and will increase the installation complexity.

B. Fuel Saving Using the Warning System

In order to evaluate the reduction of inefficient areas achieved when using the proposed warning-driving assistant, 120 test drives have been performed, using five different models of vehicles with six different drivers. Each driver followed 40 times the same route, half of them without using the assistant, and then following the warning advice provided by the assistant. Tables VII–XII capture the average fuel consumption for each driver when driving without the warning assistant and when using the assistant. In addition, these tables contain the values of t-test.

TABLE VIII
T-TEST FOR DRIVER B

	Assistant Disabled	Assistant Enabled
Mean	5.99 l/100 km	5.77 l/100km
Variance	0.03	0.04
Observations	20	20
df	37	
T Stat	3.73	
P (T<=t) two tail	6.46E-04	

TABLE IX
T-TEST FOR DRIVER C

	Assistant Disabled	Assistant Enabled
Mean	8.13 l/100 km	7.61 l/100 km
Variance	0.04	0.06
Observations	20	20
Df	36	
T Stat	7.23	
P (T<=t) two tail	1.63E-08	

TABLE X
T-TEST FOR DRIVER D

	Assistant Disabled	Assistant Enabled
Mean	7.76 l/100 km	7.19 l/100 km
Variance	0.01	0.08
Observations	20	20
Df	26	
T Stat	8.51	
P (T<=t) two tail	5.39E-09	

TABLE XI
T-TEST FOR DRIVER E

	Assistant Disabled	Assistant Enabled
Mean	7.29 l/100 km	7.07 l/100 km
Variance	0.07	0.06
Observations	20	20
Df	38	
T Stat	2.72	
P (T<=t) two tail	9.76E-03	

In order to validate that the energy savings obtained are not due to random factors, the two samples t-test assuming unequal variances [42] has been used. Considering the null hypothesis as "there is no improvement in fuel consumption levels when using the eco-driving assistant" and calculating the p-value for each driver we obtain the following values: 2.08E-08 (Driver A), 6.46E-04 (Driver B), 1.63E-08 (Driver C), 5.39E-09 (Driver D), 9.76E-03 (Driver E), and 1.15E-06 (Driver F).

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TABLE XII
T-TEST FOR DRIVER F

	Assistant Disabled	Assistant Enabled
Mean	8.02	7.14
Variance	0.01	0.33
Observations	20	20
Df	21	
T Stat	6.74	
P (T<=t) two tail	1.15E-06	

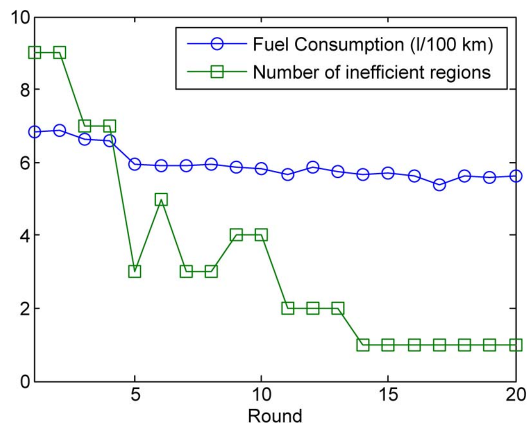

Fig. 14. Driver A: Progression of the fuel consumption and inefficient regions.

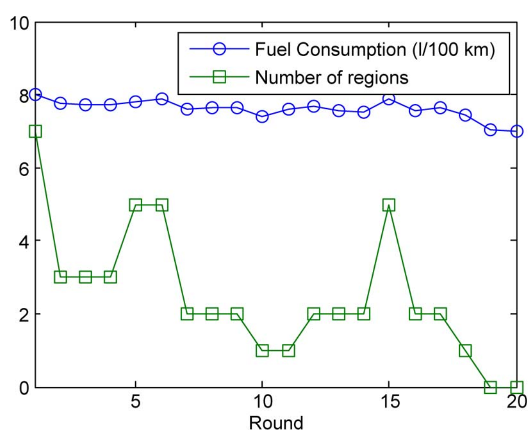

Fig. 15. Driver D: Progression of the fuel consumption and inefficient regions.

All values are below the 0.05 threshold). Therefore, the null hypothesis (under the 0.05 threshold) can be rejected.

Then, we analyzed the progression of the inefficient areas and fuel consumption. Fig. 14 captures the number of regions where the driver A realized inefficient actions and the fuel consumption, test by test, using the system proposed in the route A. Fig. 14 shows that the driver improves the fuel consumption by 17.72% and the inefficient actions are reduced by 88.88%. On route B (Fig. 15), the driver D was able to improve fuel consumption by 12.34% and decrease the inefficient actions by 100%. Finally, the route C is also improved by driver F. In Fig. 16, we can see that the fuel consumption decreased by 17.65% and the inefficient actions by 100%. We can conclude

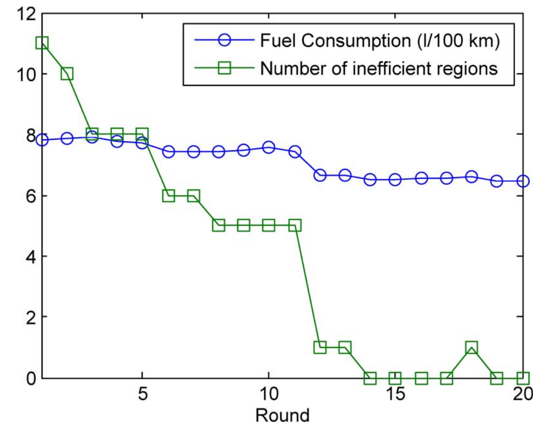

Fig. 16. Driver F: Progression of the fuel consumption and inefficient regions.

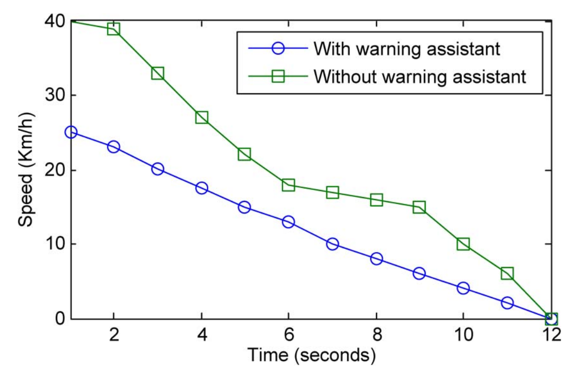

Fig. 17. Speed pattern comparison at one inefficient area with and without assistant.

that the improvement is very important, between 10% and 20% depending on the driver, route and the environment state.

These results are better than other proposed solutions such as reducing the speed [43] (6.4% of fuel saving), showing the instantaneous fuel consumption [44] (6%), sharing the fuel consumption among a specific group of users [12] (4.6%), or reporting the green house gases emissión to the drivers [45] (8%).

Other more complex proposals obtained similar results to the presented solution. However, they require a large amount of data that is difficult to obtain in real environments. Therefore, these proposals are validated in simulators as opposed to our proposal. For example, the authors in [9] propose the use of model predictive control of a vehicle in a varying road-traffic environment for ecological driving based on anticipation of the road and traffic in a crowded road network regulated by traffic signals. This model needs information about the signal phase and timing information of a traffic light. Therefore, this algorithm was tested in simulation, showing initial fuel economy and CO_2 improvements of around 12%.

The major difference introduced by the use of the warning assistant is appreciated when driver is driving in the inefficient area. The results of magnifying the deceleration pattern one of the times that the previous driver has to stop in both cases is presented in Fig. 17. This figure shows the behavior of the driver A in one of the inefficient regions. The vehicle speed is too high in the case when the warning assistant is

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disabled and the driver has to brake sharply, wasting the energy previously produced. However, when the assistant is enabled, the driver adjusts the speed and prevents the sudden slowdown. In this case, the energy demand is lower. Providing an alert to the driver when vehicle is close to the inefficient area in order to release the accelerator or change gears is positively correlated with fuel consumption savings. However, the degree of improvement depends on the skill of the driver and his or her response when receiving the recommendations. The fuel saved in Fig. 17 is around 2%. Therefore, if the trip has many inefficient areas, we will save a significant amount of fuel.

VIII. Conclusion

This paper has presented and validated the impact in fuel saving when using of an eco-driving assistant based on the discovery of areas where the driver can potentially realize inefficient actions in order to assist that driver to avoid potential inefficacies in terms of energy efficiency when crossing them. The system predicts the driver's actions in advance based on the vehicle telemetry previously obtained in that region. An MLP is employed to perform predictions.

The system minimizes the hardware installation inside the vehicle and can therefore be used on nearly any model of vehicle. We only need a mobile Android device and an OBD Bluetooth adapter for telemetry.

The eco-driving assistant has been validated in different test drives, using different models of vehicles with different drivers. The results show the positive improvement on fuel consumption when the system is used regularly by drivers. On many occasions, the areas where the driver used inefficient actions are reduced to zero. Furthermore, we have observed that one of the major benefits of the system in order to save fuel is its ability to smoothen deceleration patterns avoiding wasting fuel in fast decelerations.

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