LESY-ECO

Learning system for eco-driving based on the imitation

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Abstract: In this paper, we propose a learning method for eco-driving based on imitation. The system uses Data Envelopment Analysis (DEA) in order to calculate the driving efficiency from the point of view of the fuel consumption. The input and output parameters have been selected taking into account the Longitudinal Vehicle Dynamics Model. This technique allows us to notify the user about who is the most efficient driver close to him or her and to suggest the imitation of the behavior of such driver. The proposed method promotes learning by observation and imitation of efficient drivers in a practical rather than theoretical way such as attending eco-driving lessons. The DEA algorithm does not depend on the definition of a preconceived form of the data in order to calculate the efficiency. The DEA algorithm estimates the inefficiency of a particular DMU by comparing it to similar DMUs considered as efficient. This is very important due to the dynamic nature of the traffic. A validation experiment has been conducted with 10 participants who made 500 driving tests in Spain. The results show that combining eco-driving lessons with the proposed learning system, drivers achieve a very significant improvement on fuel saving (15.82%)

Keyword: eco-driving; intelligent transport system; Data Envelopment Analysis (DEA); driving assistant; learning system

I. INTRODUCTION

The vehicle is one of the most significant innovations of the past century. This invention has had an enormous impact at the social (Mass Production, Toyota Production System, etc.), ecological, and economic levels. The expansion of the automobile has contributed to globalization and economic growth in Europe, United States and Japan.

In recent years the vehicle fleet has experienced a tremendous growth. Between 1995 and 2005 the car park grew 22.93% in North America, a 27.36 percent in Australia and a 24.47% in OCDE countries [1].

On the other hand, many of the vehicles in circulation are old. These old models of vehicles consume more fuel and emit more greenhouse gases than the modern vehicles because their engines and the aerodynamics are less optimized. In Spain, 16% of vehicles in circulation are more than 20 years old [2].

The transport sector has an important impact on energy consumption and the emission of gaseous pollutants due to the increase in the number of vehicles in circulation and their age. This energy demand from the vehicles has very negative consequences on the economy and on the health of people.

The shortage of energy resources makes the products transported more expensive and creates dependencies between countries that lack them. Regarding the impact on the health of the citizens, the consequence of this high energy demand from the vehicles is materialized in an increase in the death rate due to the high levels of pollution.

Many works highlight that there are more deaths due to contamination caused by vehicles than by road traffic accidents. In "Traffic: civilization or barbarism" report, the authors [3] conclude that the most deadly effect of driving is the pollution from vehicles which causes five times more deaths than accidents themselves. Another example can be found in [4] where the authors conducted a study about the impact of pollution on premature deaths in the United States. The conclusion was that the transport sector is the most responsible for premature deaths (53,000 per year) along with the electric power generation sector (50,000 per year). In addition, they observed that vehicles' pollution produces 30% more deaths than traffic accidents.

This context proves the importance of reducing fuel consumption in order to improve the health of citizens and minimize the economic costs. It is necessary to decrease the fuel demand to minimize the impact of vehicles on the environment. Solutions to do this can be based on technology (weight reduction, engine optimization, aerodynamic improvements, etc.), the behavior of the driver (eco-driving) or the selection of the optimal route (eco-routing).

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 vehicle's technology [5] [6]. 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 addition to the energy saving, an eco-driving style has other advantages such as:

- Increasing the lifetime of the vehicle components

- Reducing the pollutant gas emissions

– Decreasing the driver stress

– Decreasing the risk and severity of traffic accidents

– Improving the traffic flow

One of the most important research lines about eco-driving is focused on the learning methods to help the user to drive efficiently. The driving requires the user to perform several actions at the same time, so the cognitive load is very high and the user acquires automation. Therefore, it is very difficult to change bad driving habits. Researchers show that users tend to return to their previous driving style when they finish the learning period. This paper proposes to use a learning system based on imitation. The assistant informs the user about the efficiency of nearby drivers and indicates that he or she should try to follow them. This solution allows users to observe how they should behave in a real environment and in a specific situation to save fuel as opposed to other alternatives such as classes or simulators.

The two main contributions of this work are the proposal of a method to obtain an optimal driving profile that takes into account the environment state and the impact of preceding vehicle information on fuel consumption reduction. Although a lot of research into eco-driving has so far focused on the effects on the vehicle being driven, few quantitative evaluations have been made regarding the effects on vehicles which follow the eco-driven vehicle [7].

II. LESY-ECO SYSTEM

This paper proposes a learning system based on imitation in order to improve the driver's driving style from the point of view of energy efficiency. The solution estimates the efficiency of nearby drivers based on real-time measured vehicles' telemetry and notifies the user.

Vehicles' telemetry is obtained through the OBD2 diagnostic port and is sent to an Android mobile device. This port is included in almost all models of vehicles. In the U.S., since 1996 [8], it is mandatory in gasoline vehicles (1997 for diesel vehicles). Then, the mobile device sends the vehicles' telemetry data to a server.

On the server, Data Envelopment Analysis (DEA) [9] is used to calculate the efficiency of driving. This technique calculates the inefficiency of the driver by comparing it to nearby drivers considered as efficient. This feature is very important because other solutions calculate efficiency values associating the input variables with statistical averages that may not be applicable to the current driver's context due to the dynamic nature of traffic.

Finally, the system warns to the driver about who are the best drivers from the point of view of energy saving and suggests that he or she imitates their driving behavior. The solution provides information (registration number, color and manufacturer) about the best vehicle using the loudspeaker in order to spot and track it. At the same time, the screen from the mobile phone shows the average speed, average acceleration, average deceleration, and the fuel consumption rate obtained by the user and compares them to the best driver. Figure 1 captures the user interface.

On the other hand, the system checks the distance between the vehicle's user and the vehicle selected by DEA algorithm. If the distance exceeds a limit, the solution runs the algorithm again to obtain the best close driver.

In addition, the system issues feedback in real-time when the driver does not comply with the eco-driving rules. Real-time feedback is very effective since it allows the user to correct the negative actions without having to remember the eco-driving tips provided by eco-driving systems.

The main research question addressed by the proposed system is to validate and quantify the positive impact on fuel consumption when the user tries to imitate the behavior of an efficient driver. Figure 1 shows a schema of the proposed system. In the following subsections, we describe each component of the solution.

III. DATA ACQUISITION SYSTEM

To obtain the vehicle diagnostic values, we connected a Bluetooth adapter to the OBD2 port [10]. OBD is a port that allows evaluating the emission of greenhouse gases and doing in-depth diagnostic about the operation of vehicle. A mobile device sends a PID to the Bluetooth adapter. A PID is just an identifier. For example, vehicle speed is PID "0D" .The 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.
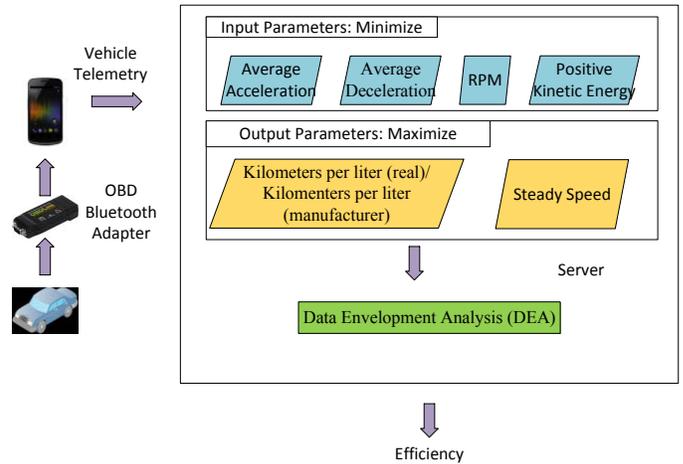

Fig. 1. LESY-ECO System

Finally, the Bluetooth adapter reads the response, and sends it to the mobile device. In our proposal, we monitor the following variables:

Speed: It is obtained with the "0D" PID. This variable allows us to:

– Estimate the acceleration

– Estimate the deceleration

– Infer the driving time at a constant speed

– Estimate the positive kinetic energy

Engine Speed: It is obtained with the "0C" PID. This variable is employed to assess the driving efficiency.

Fuel Consumption: This variable is used for cross-validation. Some vehicles provide an indicator for the engine fuel rate (PID 5E; liters/hour) through the OBD2 port, but fuel flow sensor information is not always available through the OBD2 port. However, we can estimate the fuel consumption from other sources such as the mass air flow (MAF) sensor, the air/fuel ratio, RPM, effective pressure (MEP), and the fuel consumption map of the specific car. We can find in-depth information about how to estimate fuel consumption/CO2 emission from OBD sensor data and what are the potential problems in [11]. In our case, we estimate the fuel consumption using the speed and the MAF (mass air flow) sensors [12].

IV. DATA ENVELOPMENT ANALYSIS (DEA)

Data envelopment analysis (DEA) is a linear programming methodology to estimate the efficiency of multiple decision-making units (DMUs) when the production process presents a structure of multiple inputs and outputs. This method was proposed by Charnes, Cooper, and Rhodes [13].

DMU [14] is defined as the entity responsible for converting inputs into outputs and whose performances are to be evaluated. DMUs may include banks, department stores, supermarkets, hospitals, students, drivers, vehicles, and so on. A group of DMUs is used to evaluate each other with each DMU having a certain degree of managerial freedom in decision making. This method allows us to make relative comparisons. DMUs have the following features:

– Numerical data are available for each input and output.

– The DEA elements (inputs, outputs and choice of DMUs) should show an analyst's or a manager's interest.

– The measurement units of the different inputs and outputs need not be congruent.

In our proposal, each DMU represents a different driver. The objective is to obtain the efficiency of each user. Drivers whose efficiency values are higher are those who act as models for the rest of the drivers. If we consider a set of drivers "n" (DMUn), each of them with an "I" number of inputs and "O" number of outputs, the efficiency measure E_k for DMU$_k$ (driver K) is calculated by solving the following linear programming model.

Maximize:

$$E_k = \frac{\sum_{r=1}^{O} u_r y_{rk}}{\sum_{i=1}^{I} v_i x_{ik}} \tag{1}$$

Subject to:

$$\frac{\sum_{r=1}^{O} u_r y_{rk}}{\sum_{i=1}^{I} v_i x_{ik}} \leq 1 \tag{2}$$

$$u_r \geq 0; \; v_i \geq 0 \tag{3}$$

where y_{rk} is the selected output of each variable (e.g.: Driving time at steady time) from the driver "k", x_{ik} is the selected input of each variable (e.g.: Average Acceleration) from the driver "k", and v_i, u_r are the weight factors and are determined for each DMU. Therefore, we have to solve the linear programming model "n" times, once for each driver. The driver is considered to be inefficient when E_k is less than 1. Instead, when the driver is applying the eco-driving rules E_k is 1.

One of the main advantages of this solution is that there is no preconceived form on the data in order to calculate the efficiency. DEA estimates the inefficiency in a particular DMU by comparing it to similarly DMUs considered as efficient. Other solutions estimate the efficiency associating the values of the entity with statistical averages that may not be applicable to that context.

This feature is very useful in the driving context due to its dynamic nature. We want to compare the driving of a set of drivers in a particular situation and at a specific location. In this case, the traditional statistical models can produce inaccurate results. It is not fair to compare the driving under different traffic and weather conditions. For example, if the traffic is heavy, traditional algorithms might conclude that all drivers are inefficient when we associate the results of drivers with average values. However, in this drivers' set could be some who drive better that others from the viewpoint of energy efficiency, but the road conditions make impossible that he or she obtains results close to the mean values.

The main problem of DEA is with the unreliable data because the DMUs considered as efficient determine the efficient frontier. Therefore, the efficiency of the rest of DMUs depends on this frontier. Another problem is that an efficient DMU does not necessarily produce the maximum output possible for a given level of input. Finally, the number of efficient units on the frontier tends to increase with the number of inputs and output variables [15].

In recent years, many authors have applied this technique to evaluate the performance in the power sector and organizations such as: hospitals, universities, courts, police forces departments and banks. This method has shown positive results in multiple scenarios [16] [17].

A. Input and Output Parameters

The election of input and output parameters is very important because they directly affect the accuracy of the results. We have to identify which variables affect fuel consumption and to which extend. In our case, the selection is based on the longitudinal dynamics of the vehicle [18] [21]. The result of an increase in the value of these variables is independent of the vehicle type. On the other hand, sometimes it is difficult that there are vehicles with similar characteristics. For this reasons, the different car type or engine type is not considered.

Alternatively, we could use Data Clustering Algorithms such as Expectation–maximization algorithm [19] before run the DEA algorithm. This algorithm would take into account the characteristics of the vehicle to build the groups. In this case, the DMUs would only be formed by vehicles belonging to the same cluster.

Input parameters:

– Average Acceleration

– Average Deceleration

– Percentage of time that engine speed is not in the optimal range

– PKE (Positive Kinetic Energy): It is calculated using the following equation [17] [18]:

$$PKE = \frac{\sum(v_i - v_{i-1})^2}{d} \; ; \; v_{i-1} < v_i \qquad (4)$$

where v is the vehicle speed (m/s) and d is the trip distance (meters) between v_i and v_{i-1}.

Output parameters:

– Kilometers per liter (real) / Kilometers per liter (Manufacturer)

– Driving time at steady velocity

V. SYSTEM VALIDATION

A. Experiment configuration

The eco-driving assistant was deployed on Android mobile devices: Nexus S, Nexus 7, Galaxy Nexus and Htc One V. Nexus S and Htc One V are equipped with an ArmV7 processor at 1 GHz, 512 MB of RAM. Nexus 7 has a Tegra 3 processor at 1.2 GHz and 1GB of RAM. Galaxy Nexus has a ArmV9 processor at 1.2 Ghz and 1 GB of RAM.

The OBDLink OBD Interface Unit from ScanTool.Net [20] was used to get the relevant data (vehicle speed, fuel consumption, engine speed and acceleration) 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.

In order to evaluate the energy savings achieved with the proposed system, 500 test drives have been performed with 10 different drivers. The tests were performed in Granada between the months of January to April 2014. The selected route has both parts of urban road and a highway. The route length is 8.3 Km. This track is composed of a 36.64% of highway and a 63.86% of urban road. The trip time estimated by Google under normal conditions is 18 minutes. All tests were made under similar conditions (time, traffic, and weather). The vehicles employed were all Citroen Xsara Picasso 2.0 HDI.

Drivers were divided into two groups: control and experimental. Users from the control group did not have enabled the proposed system. In this case, drivers only received classic eco-driving tips. For example, the assistant alerted those users when it detected that the vehicle speed exceeded a limit.

In contrast, drivers from the experimental group had the LESY-ECO solution activated. The system reports to the users about who is the best nearby driver in order for he or she to imitate their behavior.

The experiment consisted of three phases. In the first phase drivers completed the route 20 times without the use of any vehicle of reference (the user was driving as usual).

In the second phase, all drivers (control and experimental group) received eco-driving lessons. Finally, the drivers had to complete 30 laps in third phase. In this case, drivers from control group only received classic eco-driving tips in real time, while users from experimental were also notified about the best close driver from the viewpoint of energy saving.

B. Experimental Group Results

Figure 2, 3, 4 show the average deceleration, positive kinetic energy and fuel consumption, respectively. The blue columns capture the average value obtained by the driver for each variable before receiving the eco-driving lessons (first phase). The orange columns capture the results after the eco-driving lessons and with the proposed system activated.

Experimental group improves all of the variables that influence fuel consumption. It is important to highlight that users from this group reduce the frequency and intensity of the slowdowns. The sudden accelerations have a negative effect on energy consumption when they are followed by downturns. In these cases the energy is unused as lost heat through the brakes of the vehicle. We can observe that drivers decrease both accelerations and decelerations. Therefore, the fuel consumption is lower. The improvement in fuel consumption when using the LESY-ECO SYSTEM was 15.82% on average.
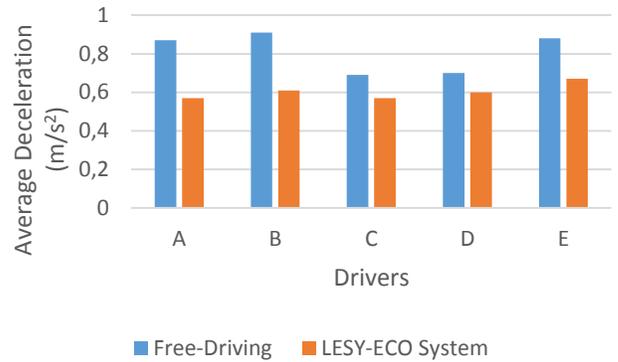

Fig. 2. Average Deceleration obtained by drivers from experimental group with and without LESY-ECO System .
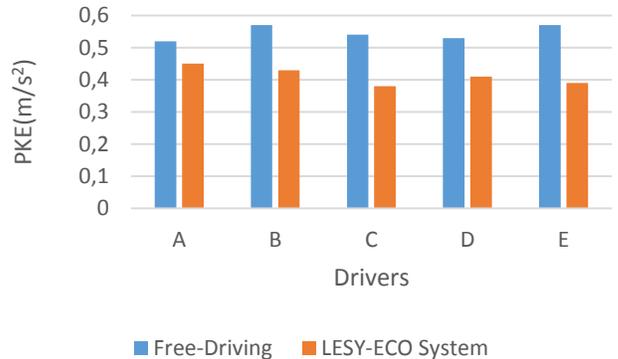

Fig. 3. Positive Kinetic Energy obtained by drivers from experimental group with and without LESY-ECO System.
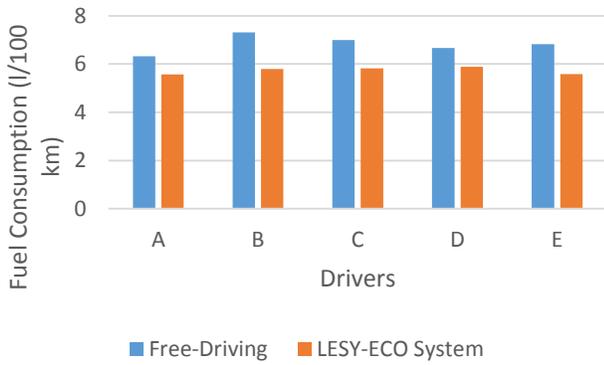
Fig. 4. Fuel Consumption obtained by drivers from experimental group with and without LESY-ECO System.

Figure 5 compares the speed profiles obtained by one of the drivers with and without the reference vehicle. The reference vehicle was obtained using the DEA method. Looking at the figure, you can see that:

– Vehicle Speed decreases when it follows the reference vehicle (orange line).

– Driver was driving at an average speed of 80 Km/h between 1.43 and 3.95 kilometers, while when it drove freely the speed reached 100 Km/h during a short period of time and the driver had to stop, therefore, wasting energy.

– Between the kilometers 0-1 and 4-8.3 the number and intensity of the accelerations (positive and negative) decreased.

– Driving time at steady speed increases when the user follows the efficient driver. In this case, the fuel consumption decreases, since the acceleration resistance that is proportional to the vehicle weight disappears and so does the intensity of the acceleration. In addition, the energy is not wasted as heat.
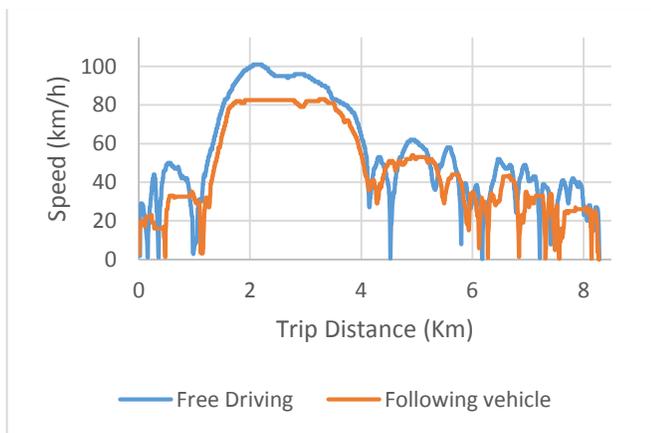

Fig. 5. Speed profiles with (following vehicle) and without (free driving) the LESY-ECO system.

C. Control Group Results

Figures 6-8 show the results obtained by the control group. The blue columns capture the average value obtained by the driver for each variable before receiving the eco-driving lessons. The orange columns capture the results after the eco-driving classes.
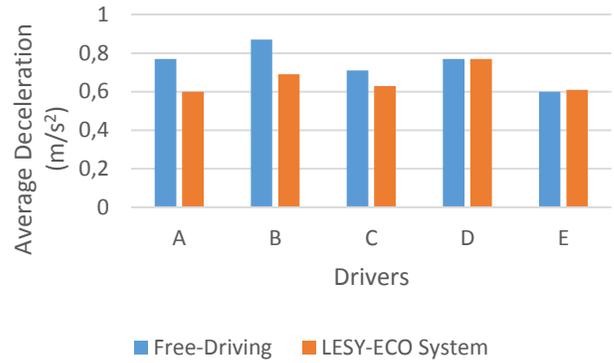

Fig. 6. Average Deceleration obtained by drivers from control group with and without LESY-ECO System .
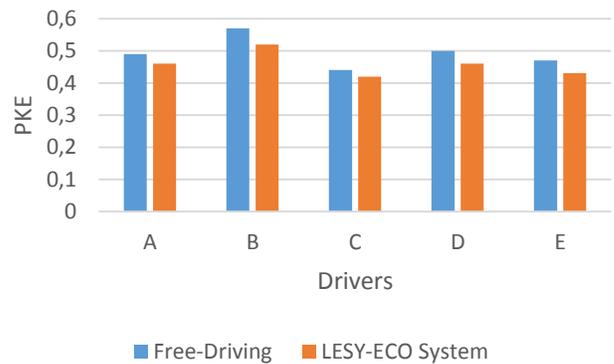

Fig. 7. Positive Kinetic Energy obtained by drivers from control group with and without LESY-ECO System.

Fig. 8. Fuel Consumption obtained by drivers from control group with and without LESY-ECO System.

We can see that there are not many changes on the driving. Fuel economy was 3.56% on average for these drivers. This improvement in fuel consumption is less than that obtained by the learning system (15.82%) proposed in this paper.

On the other hand, the frequency and intensity of the accelerations (positive kinetic energy) do not experience significant variations. The values only decreased 7% on average. Also, it can be observed that in some cases the average decelerations do not improve (driver D and E).

IV. CONCLUSIONS

In this paper, we have proposed a learning method for eco-driving based on the imitation of efficient nearby drivers. The system estimates the efficiency of each driver using the vehicle telemetry data obtained in real-time and using the Data Envelopment Analysis (DEA) algorithm. The input and output parameters have been selected taking into account the Longitudinal Vehicle Dynamics Model [18] [21]. DEA is very useful in this context because it is not based on the comparison with average values. The DEA algorithm estimates the inefficiency in a particular DMU by comparing it to similarly DMUs considered as efficient. This is very important due to the dynamic nature of the traffic. The solution informs each driver about who is the best nearby driver (in terms of energy efficiency) and suggests that he or she imitates the behavior of such efficient driver. Therefore, the driver can observe how he or she should behave in a specific situation and location. This facilitates the learning from the user.

The learning method has been validated using different test drives and users. The results show a significant positive impact on driving and fuel economy when we combine eco-driving lessons with our LESY-ECO system. On the other hand, drivers which only received lessons did not made major changes on their driving style and the improvement on fuel consumption was very low.

As future work, we want to observe the effect of the solution in driving habits with a larger number of drivers, during a longer period of time, and under different road conditions. Furthermore, we want to analyze different ways to warn the user about who is the most efficient driver such as sound notifications, virtual reality, vibration patterns, and so on.

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