Eco-driving Profiling and Behavioral Shifts Using IoT Vehicular Sensors Combined with Serious Games

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Abstract*— In addition to smarter road vehicles and smarter roads, more smartly human driven vehicles (that are as yet still predominantly more common-place than autonomously driven ones) currently still have a huge potential to improve road safety, fuel efficiency and to reduce vehicle exhaust emissions. In this work, we propose a human driving profiling algorithm with the means of Serious Games (SGs) – games for training and learning drivers' trip purpose beyond a behavioral improvement via users' motivation and engagement in a digital environment – to assist the driver in promoting more fuel efficient (low fuel consumption, FC) driving. The game supplies drivers or players with direct feedback when more inefficient, and riskier, driving manoeuvres are detectable, via sensing and analysing the changes of throttle position, engine revolutions per minute (RPM), car speed and jerks (changes in acceleration with respect to time). Such manoeuvres derived from the On-Board Diagnostic-II interface to the vehicle sensors complemented by additional sensors such as GPS location, e.g., from a mobile phone or inbuilt vehicle sensor, can be regarded as eco-driving events. Providing eco-driving feedback via the user interface of a SG, keeps the driver aware of the fuel economy and safety. We also argue that evaluating the driving style for the whole trip allows us to take into account how the dynamic driving behavior is sometimes affected by other factors (e.g., traffic congestion). In addition, this quantitative evaluation is important as a gaming mechanism, i.e., an updated score can facilitate reaching a higher gaming level, etc. In contrast to existing studies, we combine fuel efficiency with the throttle position values in the eco-driving classification module. We have done some initial analysis for this, using the naturalistic historical driving data from the enviroCar project's open data initiative. We reason that throttle position is the most powerful indicator of fuel efficiency and driving style among the other studied parameters.

***Keywords* — Eco-driving, gamification, Serious Games (SG), Internet of Things (IoT), driving pattern, fuel consumption (FC), fuel efficiency, feedback, On-Board Diagnostics-II (OBD-II);**

I. INTRODUCTION

The road transportation sector is still growing worldwide and the major consumer of oil that predominantly results in greenhouse gases increasing, having serious effects on both human health and the earth. Hence, there is an urgent societal need to reduce fossil fuel emissions from the road transportation sector [1]. Vehicle drivers have significant margins to improve safety and reduce emissions [2][3][4]. They can save up to 25% of fuel by adopting efficient driving patterns [5][6][7], depending on the type of vehicle [8]. Thus, over the last few years, interest has been raised in monitoring vehicles and driving data in different application contexts, aiming to identify driving situations and manoeuvres that are risky, reduce the energy efficiency, and increase engine emissions. For example, with fleet management domain, its administrators are keen on reviewing their drivers' driving styles through gathering more finely-grained information about fleet usage, which is influenced by driving patterns. Also, car insurance firms could place insurance premiums (additional costs) based on someone's past driving records (Pay-As-You-Drive). In addition, more recently governments may require drivers to drive more efficiently in order to receive a driving license, e.g., in Spain [8]. Moreover, characterizing human driving pattern is fundamental in the application of modern transportation services such as the application of artificial intelligence in the transport sector, and the connected autonomous vehicles for safer (e.g., reduce the human errors), cleaner, smarter and more efficient transport modes [9][10].

Eco-driving (economic or ecologic driving) is an approach, in which decision-making is based upon an understanding of what primarily affects fuel consumption, including recommendations concerning a person's driving attitude (decreasing acceleration, braking, idling, speeding and driving aggressively), the way and frequency a vehicle is used, and its configuration [11]. Studies have demonstrated the effectiveness of an eco-driving support system in saving fuel, e.g., [12]. There are five common eco-driving rules related to driving style, which have been shown to have a significant effect on vehicle fuel consumption and emissions: (1) Avoid rapid starts and accelerate smoothly; (2) Decelerate smoothly by releasing the accelerator in time while leaving the car in gear; (3) Maintain a steady speed by anticipating traffic flow; (4) shut down the engine for longer stops; (5) Shift up gear as soon as possible and avoid engine revolutions at a high level [13]. However, safety should be considered cautiously since some eco-driving tactics may affect safety [11][14], e.g., coasting that encourages to avoid the use of brakes as possible while driving, or accelerating too slowly whilst overtaking on a single lane road.

Providing continuous feedback to the design of eco-driving assistants is recommended to improve the effects achieved by learning [15][16]. [7] highlighted the need to

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continuously motivate the drivers toward eco-driving styles, showing that eco-driving advice can decrease fuel consumption (FC) from 5 to 25%. Whilst, on some occasions, drivers adopt a less efficient driving style than the one they previously had, if they misinterpret such advice [8]. Hence, the need for easy to understand, practical advice.

We believe that encouraging drivers to improve how they eco-drive could be promoted using gamification. Gamification term refers to the application of game-style mechanics and experience designs in non-game contexts and activities, to digitally engage and encourage participation with a positive behavior motivation (as virtual reward systems) to achieve the desired goal [17][18][19]. According to [20], a gameful design can motivate positive involvement. Gamification has trialled in the automotive industry for its motivating and inspiring potential [21][22]. Of course, given the frequently critical operation context, the user experience should be friendly, usable, beneficial and attractive towards the game's sustainability for retaining and gaining users. Furthermore, serious implications in terms of distraction and citizen privacy violation [23][24] should be carefully taken into account in the design and deployment of such games.

A Serious Game (SG) presents a step beyond gamification. Whereas gamification takes elements, e.g., point scoring, to improve aspects of the experience, e.g., motivation, it's not a game in itself. In contrast, SG is designed to be a game that is not solely entertainment based. A SG is a promising approach to training and learning more than entertainment, aiming at user motivation and behavior improvement, all while having fun in a digital gaming environment [25]. The diffusion of low-cost Internet of Things (IoT) devices, is enabling a new generation of games related to field operations [26]. For instance, in the road-traffic area, there are simulation-based games already supporting learning and practicing [27], while a new generation of IoT-enabled games has arisen supporting real-time interactions in the application situation [28] (e.g., a driving game on smartphones equipped with inertial sensors [29][30]).

In Reality-Enhanced Serious Gaming (RESG) – a specialization of pervasive gaming – games are fed with data collected from the field in real-time to improve the player experience with the actual activities [31]. Hence, field users' performance becomes a key factor [32] that should be easily understandable in order to supply coaching feedback to players. Adding to this, game inputs and assessment information should be easily accessible for a wide diffusion of the game. Hence, we relied on the On-Board Diagnostics-II (OBD-II) interface [33] to provide the sensor inputs as a fundamental asset for an automotive game context.

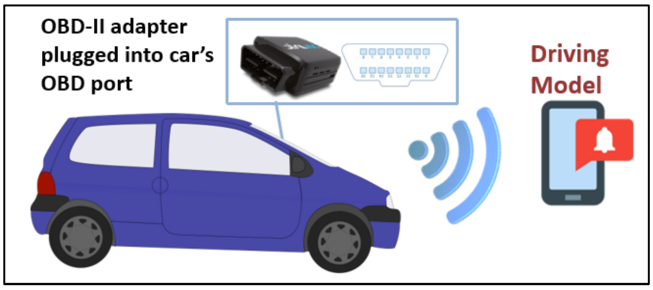

Fig. 1. Eco-driving assistant framework.

In this paper, we present a module to be pluggable into driving SGs (e.g., [28]), for encouraging the drivers or players to drive in an eco-friendlier style. During a drive, the values of car speed, throttle position sensor (TPS), engine speed (RPM) and fuel consumption are captured periodically on a smartphone connected via Bluetooth to the vehicle OBD-II interface through an adapter (Fig. 1). Given the effectiveness of monitoring a driver's behavior [34], the module supplies the driver or player with direct text feedback considering what actions he or she could do toward eco-friendlier attitude via (1) TPS, (2) car speed, (3) RPM and (4) jerks (changes in acceleration with respect to time). Significant changes in these act as events to be detected that affect FC, e.g., detecting drivers overtaking. The game also provides real-time voice prompts that lessens users' attention away from driving, else the use of SGs in the automotive domain may distract the driver, resulting in violations of traffic laws [35].

During a trip, some driving circumstances transform the driver from a fuel saver to carelessness, leading to wasting more fuel, such as encountering a pothole or roadblocks or stop traffic light timings. It's beneficial to provide an eco-driving score on a scale of 100 for the trip (100 is the best possible score), together with a summary report for the driving pattern. Moreover, this quantitative evaluation is important as an ongoing updated score, or to facilitate reaching a higher gaming level, or as a player's energy, etc. Based on the final score, the driving style can be classified with respect to three classes, fuel 'Saver', 'Typical' and 'Careless'.

In eco-driving profiling, fuel efficiency is the most important metric. Although, other factors can also lead to an increased FC in addition to driving styles, such as traffic congestion, atmospheric pressure and weather conditions, or a higher engine load occurs because of the car configuration (e.g., use of heated seats, headlights) [2], it's difficult to acquire and fuse the sensor data for these. Hence, the focus here is on the TPS values with respect to the fuel efficiency for the ecological driving classification procedure for each trip. This feature is directly controllable by the driver, reflecting his or her driving attitude in dealing with the accelerator pedal (acceleration or deceleration), which is a strong metric in the driving evaluation process [11][36]. Moreover, it impacts roughly the fuel economy and its evaluation is easy, ranging from 0 to 100 (describing saver to careless driving style). In this work, we relied on some data extracted from the enviroCar project that makes available naturalistic historical open data [37].

The remainder of the paper is organized as follows: Section 2 reviews the literature; Section 3 presents the driving data; Section 4 describes the event detectors and the eco-driving classification process; Section 5 presents a case study and discussion; Conclusions and future works are drawn in Section 6.

II. LITERATURE REVIEW

In the literature, several studies have shown the benefits of providing eco-driving advice in reducing FC and emissions with different approaches. [38] proposed a control strategy to drive efficiently by determining the adequate speed and gear at any given time. [39] relied on car speed and TPS to classify the driving styles in five levels using two techniques: Fuzzy Logic (FL), and with statistics. [40] presented a driver scoring mechanism (over 100), that uses smartphone sensor data (including accelerometers and GPS), based on overspeed, acceleration and steering events, using FL. [41] proposed two approaches for categorizing driver aggressiveness into three classes (with a score over 100) via vehicle acceleration and car jerk extracted from the GPS velocity. [36] presented a driver evaluation system for assessing driver's skills with a score over 100, based upon the achieved fuel efficiency and acceleration using in-mobile sensors and car's OBD-II system. [42] presented an algorithm for online driving classification comprising three classes for vehicle power management application using jerk. [43] developed a smartphone fuzzy application to reduce energy consumption via providing hints to drivers, considering average, minimum and maximum values of speed, acceleration and FC, derived from GPS and CAN-bus information. [44] showed an average improvement of the fuel economy by 6% on city streets and by 1% on highways, by providing direct fuel economy feedback from an on-board eco-driving device to 20 drivers in Southern California.

Studies have also used gamification's motivation towards more fuel-efficient and safer driver behavior. [45] presented a Windows Phone application to report road accidents using a game layer to motivate drivers through points, levels, challenges and other means. Some motivation for fuel saving was achieved by combining gamification with social networks. For example, [46] developed an approach for utilizing FC data in an incentive system for the Tampere City Transport company, based on comparing individual driver's average of FC with the average FC of all drivers in a specific group (formed with similar vehicles, routes, and time of day). [47] presented a social awareness system to promote eco-driving and safe-driving by implementing some social experiments on a website through communication technology to gather information about the driving styles using both GPS and motions sensors. [8] implemented a driving awareness game to encourage drivers to save fuel using some eco-driving tips, by comparing the vehicle telemetry with other users with similar characteristics. Scores were assigned to users from the energy efficiency point of view, and then users are grouped for comparison based upon several metrics such as time, average speed and the stop rate. Drivers can share their scores with other users or on social networks. The results of their experiments recorded on three different routes by 36 drivers, showed that gamification tools and eco-driving assistants help drivers to not lose interest in fuel saving.

III. SENSOR DATA

We consider indices based upon the car OBD-II interface and smartphone GPS data. In contrast to previous studies, we combined the fuel efficiency with the TPS values in the eco-driving classification to better achieve personalized ecological driving, balancing the trade-off between the impact of driving pattern and other influences on fuel economy. We chose a pluggable SG mechanism on a smartphone as part of a platform to provide a dynamic eco-driving recommendation service, and also provide a static eco-driving classification as an offline report that also highlights any eco-driving events detected.

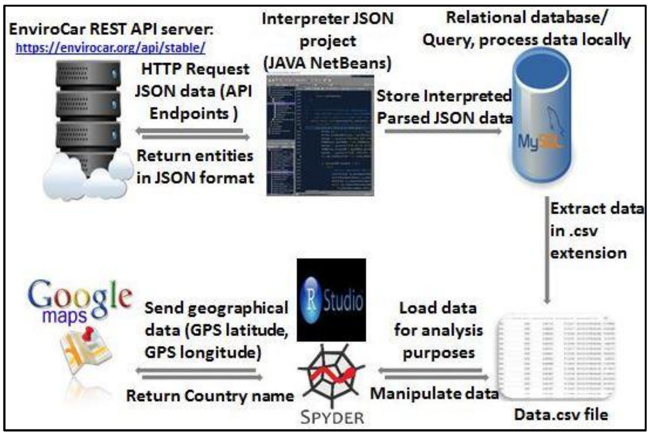

Fig. 2. Data system experimental architecture.

In this work, real-time driving simulator data is not included. However, for our experiments all used data comes from real naturalistic driving, where we relied on the enviroCar – a community-based open data collection platform for gathering pseudo-anonymized naturalistic driving vehicular sensor data (cars are just identified by ID numbers) [37]. The enviroCar community uses standard Bluetooth OBD-II adapters for reading information from the vehicle Controller Area Network or CAN bus. This information is sampled at regular time intervals (most of the tracks we used are recorded at a 5s sampling time) by an Android smartphone app, and delivered to the enviroCar server, together with GPS information for spatial-temporal analysis. Further information, like FC and Carbon dioxide (CO_2) emissions, are computed post-hoc and added on their server.

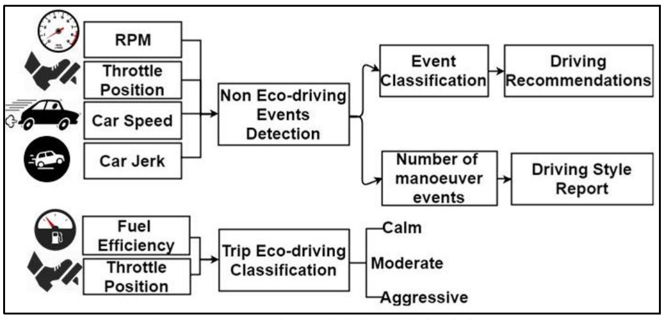

Fig. 3. Proposed eco-driving methodology.

To build our dataset, we developed a software system that requests the data through a JSON (JavaScript Object Notation) interface, using the enviroCar REST (Representational State Transfer) API via HTTP requests. Data is then stored in a local relational database for querying purposes (Fig. 2). In order to recognise the country where tracks were recorded, we used the Google Maps API[1], provided by the "*ggmap"*[2] R library, for the process of back – reverse coding[3] of a point's location (GPS latitude and longitude) into a readable address (country, locality, and route). For our analysis, we considered 8726 different gasoline tracks, with 983291 measurements for gasoline engines that were recorded mostly in Germany in the period 2012-01-01 – 2016-06-15. In order to retrace the journey of each car, an ID number identifies each of the direct features,

[1] Google Maps Platform https://cloud.google.com/maps-platform/
[2] Reverse geocode R ggmap package https://www.rdocumentation.org/packages/ggmap/versions/2.6.1/topics/revgeocode
[3] Google Maps reverse geocoding https://developers.google.com/maps/documentation/geocoding/start

besides the timestamp extracted from enviroCar smartphone application.

IV. EVENT DETECTORS AND ECO-DRIVING CLASSIFICATION

A. Non Eco-driving Events Detection

An aggressive driving pattern (such as forced acceleration) results in consuming more fuel than a normal driving style. During a drive when aggressive inefficient driving manoeuvres are identified via RPM, TPS, car speed and car jerk as depicted in Fig. 3, the module triggers driving advice in the means of warning text messages (and audio feedback for driving distraction reduction), on what actions the driver could do, to better control the fuel economy. This continuous feedback is necessary to keep the driver aware of the fuel economy. We did not involve the FC metric for the robustness of the system, due to the difficulty of its assessment, since it is affected by several internal and external factors such as car characteristics (e.g., engine size, number of cylinders, engine displacement), car weight (e.g., number of passengers), car configuration (e.g., tyre pressure, entertainment equipment use), and driving environment [2].

a) *Throttle position sensor (TPS)* (sensed from OBD-II), ranging from 0% to 100%: It is so named because it regulates the air and fuel intake into the engine, making it run slower or faster – the more the accelerator pedal is pressed (TPS value is close to 100%), the more fuel and air will be supplied to the engine and ignited. It is one of the parameters controlled directly by the driver, reflecting the driver's preferences or driving habits in dealing with the accelerator pedal. We categorized the driving style based upon this event detector into three classes calm 'C', moderate 'M' and aggressive 'A', when the value of TPS ranges in 0-39, 40-59 and 60-100 respectively (Table 1). When the instant TPS value is in the 'M' class, the game warns the driver to be careful with "Press the accelerator pedal gently for saving fuel". If the driver is pressing the accelerator pedal strongly (class 'A'), the following advice is going to be raised "Release the accelerator pedal gradually, too much fuel is supplied to the engine".

TABLE 1. DRIVING CLASSIFICATION WITH THROTTLE POSITION SENSOR.

TPS (%)	Class	Recommendation
0-39	C	-
40-59	M	Press the accelerator pedal gently for saving fuel
60- 100	A	Release the accelerator pedal gradually, too much fuel is supplied to the engine

b) *Engine speed or engine revolutions per minute or RPM* (sensed from OBD-II), expressed as the number of revolutions per minute: A strong positive correlation exists between RPM and FC: the higher the RPM, the more the fuel is consumed [2][3]. For more economic fuel, it is recommended to shift gear to stay within 2000-3000 RPM, staying less than 3500 RPM [11]. This differs from a car to another, considering several features such as engine type, engine characteristic. Table 2 shows the driving classification with this indicator. For RPM value lower than 2000, we classify the driving as calm 'C'. If the engine revolves between 2000 and 3000 times per minute, the driver is considered moderate 'M', and the game triggers a notice "Stay less than 3000 RPM to save fuel". For engine RPM value greater than 3000, careless 'CA' driving style is considered, then the module advises the player to shift to a lower RPM with "Slow down or shift up a gear to save fuel". Noting that the level of RPM's control depends on the transmission type, where full control over RPM could be achieved with manual transmission via gear selection, making the engine speeding up or slowing down (RPM is a factor of speed and gear setting [48]).

TABLE 2. DRIVING CLASSIFICATION WITH RPM.

RPM	Class	Recommendation
<2000	C	-
2000-2999	M	Stay less than 3000 RPM to save fuel
3000-	CA	Slow down or shift up a gear to save fuel

c) *Car speed* (sensed from OBD-II), measured in km/h: It is a critical input for driving analysis – a strong predictor of crash involvement, and yet it is positively correlated with FC [2]. Adding to that, overspeed is a crucial metric to characterize the driver safety compliance toward himself or herself, the passengers with respect to the surrounding speed limit. Overspeeding manoeuver events are triggered if the vehicle's speed is greater than the legal speed limit. However, the speed limit depends on the road category (e.g., motorway, congested urban road). In order to supply the player with instantaneous speed limit values through the game, we requested the maximum legal speed through a web service access, based on OpenStreetMap[4] (OSM) with GPS latitude and longitude for each sample as real-time context information ("maxspeed" tag of the JSON response). Table 3 presents the driving classification with this indicator. The driver is classified by moderate 'M' if he or she obeys the legal speed limit: car speed is less than or equal to the maximum speed. In case the car's speed reaches the allowed speed limit, the gaming module triggers a notification with the context "Be careful, reaching the legal speed limit". Yet, when exceeding the speed limit, the game warns the driver via "overspeeding, slow down for safety and fuel saving" with the exceeding value (the difference between current speed and the speed limit). In this situation, the driver is considered aggressive 'A'. We experienced that the legal speed limit values for some samples are not provided by OSM, this might be the reason of low GPS-accuracy of the measurements caused by a poor signal quality of the GPS satellite (e.g., losing GPS reception in a tunnel).

TABLE 3. DRIVING CLASSIFICATION WITH CAR SPEED (CS: CURRENT SPEED, MS: MAXIMUM SPEED READ FROM OPENSTREETMAP).

Speed(km/h)	Class	Recommendation
CS < MS	M	-
CS=MS	M	Be careful, reaching the legal speed limit
else	A	Overspeeding, slow down for safety and fuel saving

d) *Car jerk*: It is the variation of the acceleration during a time, measured in m/s^3. It illustrates a driver's acceleration profile such as forced acceleration that requires more fuel consumption to let the car accelerate quickly. As stated in [26], a very robust algorithm can be developed to classify the driver's style with this indicator. It is considered as one of the strongest aggressiveness predictors of crash involvement [49]. This feature was used in several driving

[4] OpenStreetMap http://www.openstreetmap.org

profiling studies e.g., [41][42][50]. OBD-II data does not supply a sensor for the jerk. As the longitudinal acceleration 'a' is not provided by the OBD-II interface and the GPS signals, we estimated it from the OBD-II car speed 's' as given in Eq. 1. Having the computed acceleration, then we estimated the jerk 'j' as in Eq. 2. The empirical findings in [51] show that a comfortable (non-jerky) driving pattern occurs when the jerk ranges from -4 m/s^3 to 3 m/s^3. We followed this suggestion as adopted in [41]. Table 4 illustrates the categorisation for the driver with this indicator. A driver is classified as moderate 'M', if the jerk value ranges in [-4 m/s^3, 3 m/s^3], or as aggressive 'A' if it is not the case. For the second option, we warn the driver with "Avoid forced acceleration" in case the jerk > 3 m/s^3 or by "Avoid sharp deceleration" in case the jerk < -4 m/s^3.

$$a(t) = \frac{s(t) - s(t-1)}{t - (t-1)} \tag{1}$$

$$j(t) = \frac{a(t) - a(t-1)}{t - (t-1)} \tag{2}$$

TABLE 4. DRIVING CLASSIFICATION WITH CAR JERK.

Car Jerk (m/s^3)	Class	Recommendation
$-4 \leq jerk \leq 3$	M	-
jerk>3	A	Avoid forced acceleration
jerk<-4	A	Avoid sharp deceleration

B. *Trip Eco-driving Classification*

The more the driving becomes eco-friendly and efficient, the higher the score (closer to 100) the player earns. The lower the score, the more the driving is inefficient and aggressive. As stated before, the final eco-driving classification for a trip is a trade-off between the two indicators, fuel efficiency (as the most important metric in eco-driving profiling) and TPS, as the expression in Eq. 3, where we considered 75% and 25% for ∝ and β respectively. The reasons of involving TPS beside the fuel efficiency metric in the proposed eco-driving classification, consist of balancing the trade-off between the impact of driving pattern and other factors on fuel economy (e.g., weather condition) [2]. This feature is related to the driving attitude (directly controllable by the driver or player), roughly impacts the fuel economy, its evaluation is easy to consider ranging from 0 to 100 describing saving to careless driving pattern. We reason that it is the most powerful indicator of fuel efficiency and driving style among the other studied parameters.

There are three possible classes in our eco-driving profiling module: (1) Saver 'S' for a score is in the range 60-100 representing the most efficient driving style; (2) Typical 'T' if the score value is in the range 40-59, categorizing a moderate driving pattern within a less fuel efficient group; (3) Careless 'C' with a score is in the range 0-39 describing the worst driving behavior that is the least fuel efficient.

$$\text{EcoDriving} = \propto \text{Efficiency} + \beta\text{ThrottlePosition} \tag{3}$$

a) *Fuel efficiency score*: Fuel efficiency relates distance travelled by a vehicle and the amount of fuel consumed (Eq. 4). Manufacturers give a fuel economy figure for new cars in liters per 100 km under ideal conditions for urban, extra urban (e.g., higher speeds) and combined (a mixture of the two), which is difficult to achieve. In the analysed data, we consider FC (l/h) computed by enviroCar following the formula given in [52], focusing on gasoline engines, as enviroCar's FC estimation provides the best accuracy for gasoline [37]. When a trip starts, the driver gets 0 points, and then points are earned as the trip progresses. For estimating the score of the achieved fuel efficiency, we followed the proposed approach given by [36] (Fig. 4). The algorithm consists of comparing the fuel efficiency achieved by the driver for a drive with the highest achieved fuel efficiency by any driver, who is driving a similar car model. This avoids figuring out the maximum fuel efficiency for every car model.

$$\text{Fuel\_efficiency} = \frac{\text{kilometres travelled}}{\text{total trip fuel consumed}} \tag{4}$$

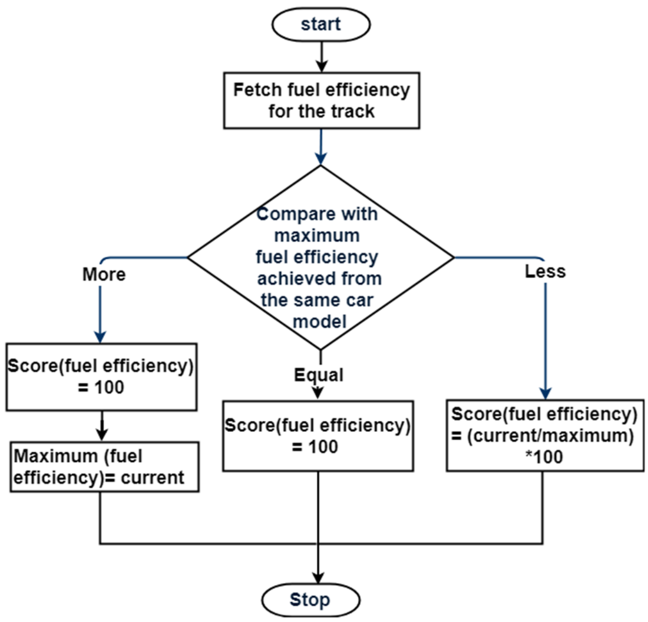

Fig. 4. Gasoline fuel efficiency score algorithm [36].

b) *Throttle position score*: The less open the throttle is, the higher the score a driver earns, given the strong positive correlation between TPS and FC as already stated in A. a). This score is given by the expression illustrated in Eq. 5. For example, if the TPS is equal to 40% at a moment, the player gets 60 out of 100 for this parameter for this specific moment.

$$\text{ThroPosit\_SC} = 100 - \text{CurrentThrotPosit} \tag{5}$$

V. CASE STUDY AND DISCUSSIONS

Our proposed SG and its scoring algorithm oriented to promote better eco-driving, are in an early stage of development. To illustrate our algorithm, we selected one of the historical tracks with 575 measurements of 71 km with an average time of 50 minutes, recorded in Germany in 2016-02-17, in the time slot 16:00-17:00. This trip was recorded with a Volkswagen Polo 9N 2009, gasoline engine. Fig. 5 presents the geographical visualization of the studied trip, while Fig. 6 shows the analysis done with RStudio[5] for the considered indicators.

It is noticeable, that the trip was mostly driven on a highway since the legal speed limit supplied by OSM, is greater than 100 km/h (except at the start and the end of the timeline) and the driver has a speed, higher than 60 km/h with no big acceleration or deceleration intervals in those cases (apart from the middle of the trace where the speed pattern went lower than 60 km/h on the highway).

There is a clear relationship between the car speed and the engine RPM over time. On the motorway, where the speed is higher than 60 km/h, the values of RPM are higher compared to urban roads at the start and the end of the trip where the OSM speed limit is about 30 km/h. To move the car at such high speeds, the vehicle engine load is higher, and it has to work harder.

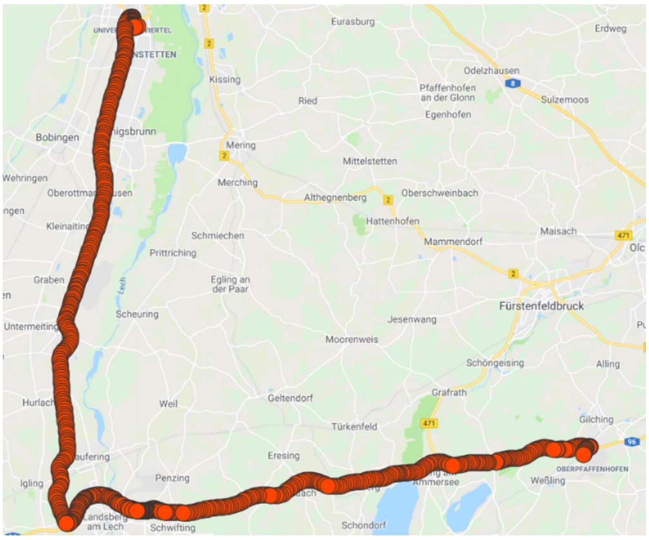

Fig. 5. Geographical visualization of the studied trip.

On the other hand, in the beginning, the middle and the end of the trip, the car moves in a stop-and-go fashion. The reason being the traffic density on an urban road in the beginning and end of the trip, where the vehicle speed adheres to the legal speed limit of less than 60 km/h. This also occurs in the motorway section which has a 120 km/h speed limit in the middle of the trip. This may be due to a traffic jam caused by an accident. In such a situation, the acceleration patterns fluctuate more than the case of highspeed travel on a highway, since on an urban road the driver has to accelerate and decelerate more when encountering traffic lights or road crossing to be in idling position, then to accelerate again letting the car to move.

The car jerk clearly depicts (fourth top plot of Fig. 6) how the driver’s acceleration profile changes over time, whether accelerating or decelerating. The jerk peaks in the case of noticeable positive variation in the acceleration or drops for the opposite scenario. For instance, at the beginning of the trip, the jerk is too high since there is a significant variation of acceleration when the driver accelerated in order to move the car from a stable to a running state.

Speeding requires a high RPM, leading to a drop in fuel efficiency. This is clear from the FC timeline of the analysed trip, where more fuel is consumed for the case of high speed. Further, the FC fluctuates more than the engine RPM on highways. This may be caused by atmospheric pressure, or engine load variations because of car configuration changes (e.g., the use of heated seats and demister blowers in cold weather since the trip was recorded at the beginning of February) or changes in the use of car accessories such as playing the entertainment system more loudly.

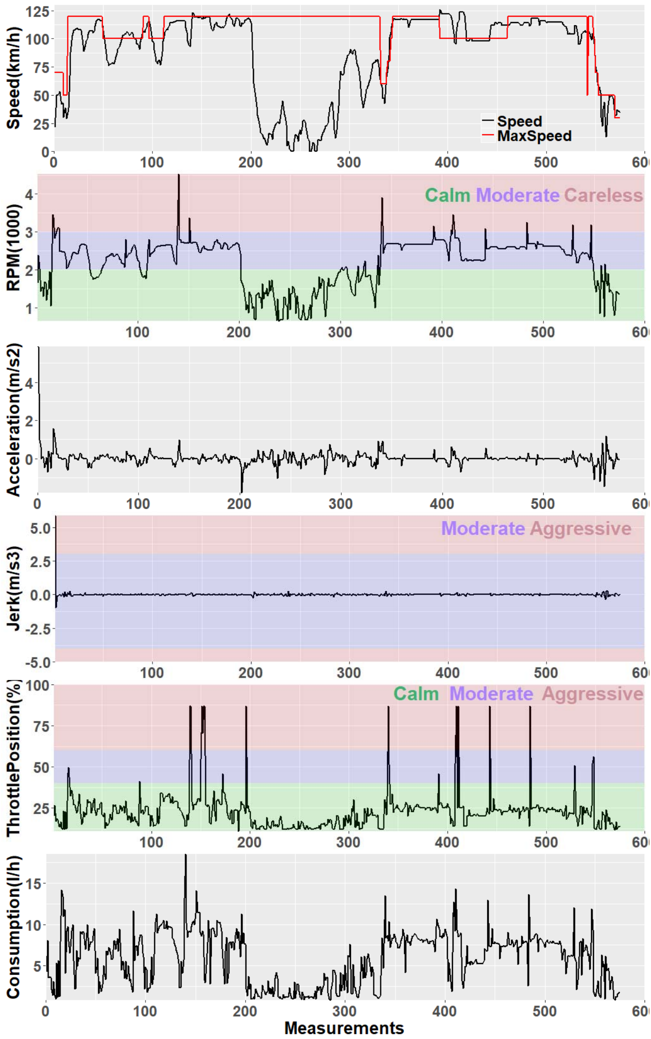

Fig. 6. Car data behavior along with the trace: car speed, RPM, acceleration, car jerk, throttle position and fuel consumption.

It is clear from the plots of both FC and throttle position (Fig. 6), that higher values of TPS are translated into higher FC values as well, regardless of the impact of other factors on FC. This is true for the opposite direction when a driver releases the accelerator pedal (resulting in a drop in TPS values), the FC values decline at those moments. This relationship is roughly close to linear, when there are spikes in TPS, there are peaks in FC pattern too and this is true for the opposite case. This validates our involvement for TPS in the eco-driving profiling process since it is directly controllable by the driver or player and it affects strongly the fuel economy.

Table 5 provides the driving classification report for each of the considered driving indices in the dynamic recommendations. The trip is considered as having moderate RPM, calm use of the accelerator pedal, with a low percentage of exceeding the permissible speed limit (15%)

[5] RStudio https://www.rstudio.com/

and with moderate changes in acceleration or deceleration (jerks).

TABLE 5. INSTANTANEOUS AGGRESSIVENESS INDICATORS REPORT.

Driving indices	*Classification*		
RPM	C: 32%	M: 65%	CA: 3%
TPS	C: 96%	M: 2%	A: 2%
Car speed	-	M: 85%	A: 15%
Car Jerk	-	M: 99.8%	A: 0.1%

Table 6 presents the overall driving classification for the analysed trip. The achieved fuel efficiency by the studied trip is 0.021 km/l/h, while the maximum efficiency achieved by 111 tracks for the same car, in the same region is 0.037 km/l/h. Hence, the score of fuel efficiency is 56.25 over 100, classified as a normal driver. The achieved score for the TPS is 77 over 100 (calm, saver driver). The eco-driving score for the trip is 61.44 over 100. The driver is considered to be a fuel saver.

TABLE 6. ECO-DRIVING CLASSIFICATION FOR THE STUDIED TRIP.

	Score/100	Eco-driving Classification
Fuel Efficiency	56.25	Normal
TPS	77	Calm
Whole Trip	61.44	Saver

VI. CONCLUSIONS AND FUTURE WORKS

The need to improve fuel efficiency and road safety is growing. A driving profiling approach has been developed in order to promote more eco-friendly driving, with the means of Serious Games, aimed at user motivation and behavior improvement. The presented gaming approach for driving profiling, might be beneficial also for insurance firms, fleet management and driving schools. The game supplies the driver or player with direct recommendations when non eco-driving events are detectable. This allows the driver or player to adapt his or her driving to reduce fuel consumption and CO_2 emissions. This direct feedback is driven from analysing the following inputs; throttle position, engine rotation speed (RPM), car speed and car jerk (changes in acceleration with respect to time). These indicators illustrate a driver's aggressiveness resulting in consuming more fuel.

After a drive, the game supplies the driver with a score between 0 (not efficient) and 100 (efficient, best score), classifying his or her ecological driving with respect to three classes, fuel 'Saver', 'Typical' and 'Careless'. In this process, we involved two indicators, (1) the achieved fuel efficiency (the most important metric in eco-driving) and (2) the throttle position. The latter directly reflects the driving style and affects strongly the fuel economy. We think that it can balance the trade-off between the impact of driving style and other influences on the fuel economy. The higher the score, the more the driving is efficient (compareding to other drivers of the same car type), and the more the driver deals carefully with the accelerator pedal (information driven from the throttle position sensor).

Our eco-driving classification module is still in the early development phase. Choosing a pluggable SG mechanism for a smartphone as a platform for providing a score for each drive, enables introducing game strategies such as ranking users based upon his or her achieved efficiency. The main focus of future work consists of finishing the development phase and real-time testing to validate the effectiveness of the proposed driving profiling. Hence, multiple drivers can be evaluated under riskier or normal driving conditions in order to observe how direct feedback affects the fuel economy while driving.

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REFERENCES

[1] ETRAC. (2014). European Road Transport Research Advisory Council. Retrieved from http://www.ertrac.org/ on 2019-05-07.

[2] R. Massoud, S. Poslad, F. Bellotti, R. Berta, K. Mehran, A. De Gloria, A fuzzy logic module to estimate a driver's fuel consumption for reality-enhanced serious games, International Journal of Serious Games, vol. 5, no. 4, pp. 45–62, 2018.

[3] R. Massoud, F. Bellotti, S. Poslad, R. Berta, and A. De Gloria, "Exploring Fuzzy Logic and Random Forest for Car Drivers' Fuel Consumption Estimation in IoT-Enabled Serious Games," IEEE International Symposium on Autonomous Decentralized Systems (ISADS), in press.

[4] J.N. Barkenbus, "Eco-driving: An overlooked climate change initiative," Energy Policy 38.2, 2010, pp. 762-769.

[5] J. Barbé, G. Boyet al., "On-board system design to optimize energy management," in Proceedings of the European Annual Conference on Human Decision-Making and Manual Control (EAM), Valenciennes, France, 2006, pp. 27–29.

[6] O. H. Koskinen, "Improving vehicle fuel economy and reducing emissions by driving technique," in 15th World Congress on Intelligent Transport Systems and ITS America's Annual MeetingITS AmericaERTICOITS JapanTransCore, 2008.

[7] J. van Mierlo, G. Maggetto, E. van de Burgwal, and R. Gense, "Driving style and traffic measures-influence on vehicle emissions and fuel consumption," Proc. Inst. Mech. Eng. D: J. Automobile Eng., vol. 218, pp. 43–50, Jan. 1, 2004.

[8] V. C. Magana and M. Munoz-Organero, "Gafu: Using a gamification tool to save fuel," IEEE Intelligent Transportation Systems Magazine, vol. 7, no. 2, pp. 58–70, 2015.

[9] C. M. Martinez, M. Heucke, F.-Y. Wang, B. Gao, and D. Cao, "Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey," IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 3, pp. 666–676, 2018.

[10] W. Wang, J. Xi, and H. Chen, "Modeling and recognizing driver behaviour based on driving data: A survey," Mathematical Problems in Engineering, vol. 2014.

[11] A. Sanguinetti, K. Kurani, and J. Davies, "The many reasons your mileage may vary: Toward a unifying typology of eco-driving behaviors," Transportation Research Part D: Transport and Environment, vol. 52, pp.73–84, 2017.

[12] X. Zhao, Y. Wu, J. Rong, and Y. Zhang, "Development of a driving simulator based eco-driving support system," Transportation Research Part C: Emerging Technologies, vol. 58, pp. 631–641, 2015.

[13] B. Beusen, S. Broekx, T. Denys, C. Beckx, B. Degraeuwe, M. Gijsbers, K. Scheepers, L. Govaerts, R. Torfs, and L. I. Panis, "Using on-board logging devices to study the longer-term impact of an eco-driving course," Transportation research part D: transport and environment, vol. 14, no. 7, pp. 514–520, 2009.

[14] A. Vaezipour, A. Rakotonirainy, and N. Haworth, “Reviewing in-vehicle systems to improve fuel efficiency and road safety,” Procedia Manufacturing, vol. 3, pp. 3192–3199, 2015.

[15] G. H. Walker, N. A. Stanton, and M. S. Young, “Hierarchical task analysis of driving: A new research tool,” in Contemporary Ergonomics, M. A. Hanson, Ed. London: Taylor and Francis, 2001, pp. 435–440.

[16] J. Tulusan, L. Soi, J. Paefgen, M. Brogle, and T. Staake, “Eco-efficient feedback technologies: Which eco-feedback types prefer drivers most?” in Proc. IEEE Int. Symp. World Wireless, Mobile Multimedia Networks, June 20–24, 2011, pp. 1–8.

[17] S. Deterding, M. Sicart, L. Nacke, K. O’Hara, and D. Dixon, “Gamification. using game-design elements in non-gaming contexts,” in CHI’11extended abstracts on human factors in computing systems. ACM, 2011, pp. 2425–2428.

[18] F. Bellotti, R. Berta, A. De Gloria, E. Lavagnino, A. Antonaci, F. M. Dagnino, and M. Ott, "A gamified short course for promoting entrepreneurship among ICT engineering students,” 13th IEEE international conference on advanced learning technologies (ICALT), 2013, pp. 31–32.

[19] S. Poslad, A. Ma, Z. Wang, and H. Mei, “Using a smart city IoT to incentivise and target shifts in mobility behaviour—Is it a piece of pie?” Sensors, vol. 15, no. 6, pp. 13 069–13 096, 2015.

[20] J. Jung, C. Schneider, and J. Valacich, “Enhancing the motivational affordance of information systems: The effects of real-time performance feedback and goal setting in group collaboration environments,” Management science, vol. 56, no. 4, pp. 724–742, 2010.

[21] R. Van Eck, “Digital game-based learning: It’s not just the digital natives who are restless,” EDUCAUSE review, vol. 41, no. 2, p. 16, 2006.

[22] I. Iacovides, “Exploring the link between player involvement and learning within digital games,” in Proceedings of the 23rd British HCI group annual conference on people and computers: Celebrating people and technology. British Computer Society, 2009, pp. 29–34.

[23] C. D. Jensen, S. Poslad, T. Dimitrakos. (Eds). Proc. 2nd Int. Conf. on Trust Management, iTrust, Lecture Notes in Computer Science (LNCS), vol. 2995, Springer-Verlag, 2004.

[24] S. Poslad, M. Hamdi, and H. Abie, “Adaptive security and privacy management for the internet of things (ASPI),” in Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication. pp. 373–378.

[25] F. Bellotti, R. Berta, and A. De Gloria, “Designing effective serious games: opportunities and challenges for research,” International Journal of Emerging Technologies in Learning (iJET), vol. 5, 2010.

[26] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of things: A survey on enabling technologies, protocols, and applications,” IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347–2376, 2015.

[27] H. Prendinger, J. Oliveira, J. Catarino, M. Madruga, and R. Prada, “ICO2: a networked game for collecting large-scale eco-driving behavior data,” IEEE Internet Computing, vol. 18, no. 3, pp. 28–35, 2014.

[28] F. Bellotti, S. Kopetzki, R. Berta, P. K. Paranthaman, G. R. Dange, P. Lytrivis, et al., “Team applications for collaborative road mobility,” IEEE Transactions on Industrial Informatics, 2018.

[29] T. O. Oshin, S. Poslad, and Z. Zhang, “Energy-efficient real-time human mobility state classification using smartphones,” IEEE Transactions on computers, vol. 64, no. 6, pp. 1680–1693, 2015.

[30] Z. Zhang and S. Poslad, “Fine-grained transportation mode recognition using mobile phones and foot force sensors,” in International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services. Springer, 2012, pp. 103–114.

[31] J. D. Fijnheer and H. van Oostendorp, “Steps to design a household energy game,” International Conference on Games and Learning Alliance, 2015, pp. 12–22.

[32] R. Drakoulis, F. Bellotti, I. Bakas, R. Berta, P. K. Paranthaman, G. R. Dange, P. Lytrivis, K. Pagle, A. De Gloria, and A. Amditis, “A Gamified Flexible Transportation Service for On-Demand Public Transport,” IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 3, pp. 921–933, 2018.

[33] S. Godavarty, S. Broyles, and M. Parten, “Interfacing to the on-board diagnostic system,” in 52nd IEEE Vehicular Technology Conference (IEEE-VTS), vol. 4.

[34] D. A. Johnson and M. M. Trivedi, “Driving style recognition using a smartphone as a sensor platform,” in 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC). IEEE, 2011, pp. 1609–1615.

[35] S. Diewald, A. Möller, L. Roalter, T. Stockinger, and M. Kranz, “Gameful design in the automotive domain: review, outlook and challenges,” in Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. ACM, 2013, pp. 262–265.

[36] S. Khedkar, A. Oswal, M. Setty, and S. Ravi, “Driver evaluation system using mobile phone and OBD-II system,” Int. J. Comput. Sci. Inf. Technol, vol. 6, no. 3, pp. 2738–2745, 2015.

[37] A. Bröring, A. Remke, C. Stasch, C. Autermann, M. Rieke, and J. Möllers, “enviroCar: A Citizen Science Platform for Analyzing and Mapping Crowd-Sourced Car Sensor Data,” Transactions in GIS, vol. 19, no. 3, pp. 362–376, 2015.

[38] Y. Saboohi and H. Farzaneh, “Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption,” Appl. Energy, vol. 86, no. 10, pp. 1925–1932, Oct. 2009.

[39] W. Wang, J. Xi, and X. Li, “Statistical pattern recognition for driving styles based on Bayesian probability and kernel density estimation,” arXiv preprint arXiv:1606.01284, 2016.

[40] G. Castignani, R. Frank, and T. Engel, “An evaluation study of driver profiling fuzzy algorithms using smartphones,” in 21st IEEE International Conference on Network Protocols (ICNP). IEEE, 2013, pp.1–6.

[41] O. Derbel et al., “Driving style assessment based on the GPS data and fuzzy inference systems,” in 2015 IEEE 12th International Multi-Conference on Systems, Signals & Devices (SSD15). IEEE, 2015, pp.1–8.

[42] Y. L. Murphey, R. Milton, and L. Kiliaris, “Driver’s style classification using jerk analysis,” in Workshop on Computational Intelligence in Vehicles and Vehicular Systems. IEEE, 2009, pp. 23–28.

[43] R. Araújo, A. Igreja, R. De Castro, and R. E. Araujo, “Driving coach: A smartphone application to evaluate driving efficient patterns,” in Intelligent Vehicles Symposium. IEEE, 2012, pp. 1005–1010.

[44] K. Boriboonsomsin, A. Vu, and M. Barth, “Eco-driving: Pilot evaluation of driving behavior changes among U.S. drivers,” Center Environ. Res. Technol., Univ. California Transportation Center, Riverside, CA, 2010.

[45] F. L. Law, Z. M. Kasirun, and C. K. Gan, “Gamification towards sustainable mobile application,” in 2011 Malaysian Conference in Software Engineering. IEEE, 2011, pp. 349–353.

[46] H. Liimatainen, “Utilization of fuel consumption data in an ecodriving incentive system for heavy-duty vehicle drivers,” IEEE Transactions on intelligent transportation systems, vol. 12, no. 4, pp. 1087–1095, 2011.

[47] R. Ando, Y. Nishihori, and D. Ochi, “Development of a system to promote eco-driving and safe-driving,” in Smart spaces and next generation wired/wireless networking. Springer, 2010, pp. 207–218.

[48] E. Ericsson, “Independent driving pattern factors and their influence on fuel-use and exhaust emission factors,” Transportation Research Part D: Transport and Environment, vol. 6, no. 5, pp. 325–345, 2001.

[49] A. B. Ellison, S. P. Greaves, and M. C. Bliemer, “Driver behaviour profiles for road safety analysis,” Accident Analysis & Prevention, vol. 76, pp.118–132, 2015.

[50] G. Castignani, T. Derrmann, R. Frank, and T. Engel, “Driver behavior profiling using smartphones: A low-cost platform for driver monitoring,” IEEE Intelligent Transportation Systems Magazine, vol. 7, no. 1, pp. 91–102, 2015.

[51] J. J. M. Molina, “Commande de l’inter-distance entre deux véhicules,” Ph.D. dissertation, Institut National Polytechnique de Grenoble-INPG, 2005.

[52] A. Faiz, C. S. Weaver, and M. P. Walsh, Air pollution from motor vehicles: standards and technologies for controlling emissions. The World Bank, 1996.