Data Analytics to Support a Smart Fleet Management Strategy

Laura Pozueco, Nishu Gupta, *Senior Member, IEEE,* Xabiel G. Pañeda, Víctor Corcoba, David Melendi, Roberto García, Abel Rionda

***Abstract*— The correct application of efficient and safe driving techniques plays an important role for professional drivers. Monitoring and analyzing driving data can promote changes in the sector in terms of better use of vehicles, reduction in energy consumption and improved on-road safety. However, the results in driving performance can vary considerably between different fleets that have received the same training in efficient and safe driving. The aim of this paper is to perform an in-depth analysis of the driving performance of professional drivers during their working day, taking into account the influence of the fleet management decisions. For this, we have selected 4 urban public transport companies with clear differences in terms of the employees scheduled and rostered drivers to bus lines. The driving behavior of 745 drivers over a period of 10 months has been evaluated considering their performance in terms of efficient and safe driving using driving patterns. A total of 6,517,983.995 kilometers of real-time driving data retrieved from vehicles every 1.5 seconds, has been analyzed. The results show significant differences in the evolution and acquisition of the new driving habits. In addition, significant observations from this paper provide valuable information for fleet managers and allow to take advantage of the data provided by the adoption of Intelligent Transportation Systems.**

***Index Terms*— data analytics, efficient driving, fleet management strategy, intelligent transportation, on-board devices, safety driving patterns**

I. INTRODUCTION

EFFICIENT driving has become one of the biggest concerns for public transport companies which invest in training courses to help professional drivers acquire new, efficient and safe habits while driving. To incorporate the new habits throughout the working day, transport companies employ efficient driving programs. These programs are designed with the aim of helping drivers gradually acquire new skills in order to be more efficient. In addition, professional drivers have certain peculiarities, such as stress or fatigue [1,2]. These variables are directly related to driving safety and can be reduced by applying efficient driving techniques. For this reason, improvements in learning methodologies are proposed, with theoretical and practical courses, feedback devices to assist while driving and periodic reports to include the continuous improvement process in learning. Moreover, fleet management and driving monitoring also allow to analyze the driving styles and establish detailed information about the use of the fleet.

Once efficient driving programs have been implemented in transport companies, the next key element is identifying the correct application of the efficient and safe habits while driving. This is an essential component for any transport company since it indicates the level of effectiveness of the driving program. For simplicity, in most cases fuel consumption is selected as a metric of driving performance. It has been proven that fuel consumption is associated with both driving patterns and road conditions. Moreover, traffic congestion and steep road slope are seen to negatively influence fuel consumption [3]. Therefore, fuel consumption can misrepresent the results of efficiency and safety performance. For that reason, our previous work focused on the design and implementation of an analytic system to evaluate efficient driving programs in professional fleets from an innovative point of view: through the analysis of driving patterns [4]. Driving patterns infer the driver's behavior from the analysis of different data. This data comes from different sources of information, including vehicular data collected in real-time such as speed, acceleration, or the use of the brake pedal. These patterns allow the fleet managers to identify the weaknesses of each driver in terms of efficiency and safety. However, if the psychological and cognitive requirements are demanding, particularly in safety-sensitive jobs, these factors should also be included in the (medical) screening of the drivers [5]. With all the collected and analyzed information, drivers receive real-time feedback in an on-board device coupled with monthly reports. With these components, a continuous improvement process in the acquisition of efficient driving habits is implemented.

However, occasionally the results are not as good as might be expected, despite the improvements in learning and evaluation methodologies. In these situations, the driving behavior analysis could detect difficulties in applying certain driving techniques (efficient or safe). When this occurs on a

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L. Pozueco, X.G. Pañeda, V. Corcoba, D. Melendi and R. García are with the Department of Computer Science, University of Oviedo, 33204 Gijón, Spain (e-mail: pozuecolaura@uniovi.es; xabiel@uniovi.es; corcobavictor@uniovi,es; melendi@uniovi.es; garciaroberto@uniovi.es).

N. Gupta is with the Department of Electronic Systems, Faculty of IES, Norwegian University of Science and Technology, Gjøvik, Norway (e-mail: nishu.gupta@ntnu.no)

A. Rionda is with AND Mobile Solutions, 33394 Gijón, Spain (e-mail: abel.rionda@adnmobilesolutions.com).

personal basis and in isolated situations, the behavior can be straightened out with custom-made reinforcement programs. Nevertheless, when the results concern the entire fleet, it is necessary to carry out a more in-depth analysis to identify the origin of the low level of driving performance. In such cases, it is necessary to complete the contextual information map, including elements such as the company's strategy (Figure 1). Therefore, Intelligent Transportation Systems (ITS) and the Internet of Things (IoT) open new opportunities to improve the traditional fleet management in the public transport sector.

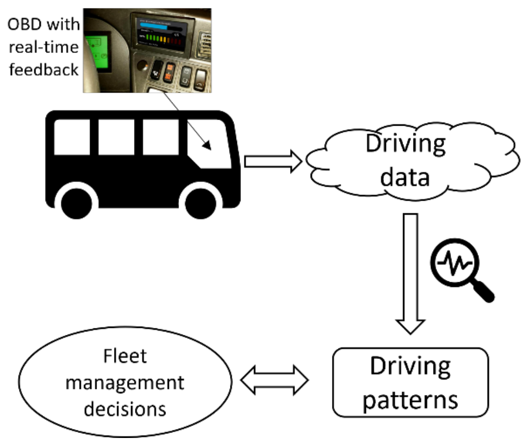


Fig. 1. Contextual information map.

In previous work [4], [6] we have already demonstrated the viability of our evaluation and analysis tool, as well as the efficient driving learning and evaluation methodology. This methodology is implemented in urban public transport companies in Spain and Morocco. 745 drivers, distributed in 4 fleets, took part in the efficient driving program. The selected companies show clear differences in terms of the total number of different bus lines assigned to each individual driver. In this paper we evaluate the overall fleet performance over a period of 10 months in terms of efficiency and safety, based on the driving patterns. For each driver, the data necessary to calculate the driving patterns are collected every 1.5 seconds throughout the entire working day. With the results, we can conclude and identify which decisions related to fleet management operation influence the driving performance results.

To the best of our knowledge, this is the most extensive analysis of driving behavior that also includes fleet management information. The results show that there are no significant differences in driving patterns related to anticipation and safe driving concerning drivers with fewer than 10 bus lines. In addition, drivers with more assigned lines also obtain acceptable results, possibly due to more cautious driving since they do not know the routes in detail. However, to obtain satisfactory results in terms of driving performance, the best fleet management strategy should be based on reducing the number of bus lines assigned to each driver.

The main contributions of this paper follow:

- We analyze the influence of the fleet management decisions on efficiency and safe driving;
- We delve deeper into the analysis of the influence of other types of contextual information related to the operational planning;
- We promote changes in the sector with the help of the analysis of the obtained data and technological advances applicable to the public transport companies;
- We evaluate the overall fleet performance over a period of 10 months in terms of efficiency and safety, based on the driving patterns.

The rest of the paper is organized as follows: Section 2 summarizes the main related works. Section 3 covers the fundamentals of the driving analysis based on driving patterns. The results are discussed in Sections 4 and 5. Conclusions and future work are summarized in Section 6.

II. Related Work

The analysis of driving efficiency has been the object of study in several papers. Commonly, the driving efficiency assessment has been represented in [7]. Recent work shows that this approach offers a biased view of efficiency and does not guarantee that drivers are applying the efficient driving recommendations while driving. In addition, the influence of other external factors on vehicle consumption are not taken into account, and there is evidence that other factors affect not only bus consumption [8] but also bus emissions [9]. To overcome the shortcomings of this approach, which is widely adopted due to its simplicity, proposals have arisen based on evaluating driving efficiency according to driver behavior. Under this paradigm, different works propose the analysis of driving behavior in greater or lesser detail.

The analysis of driving patterns involves gathering real-time driving data such as speed, rpm or accelerations [10]. Authors [11] evaluated driving behavior including different indicators, but they do not treat the data as driving patterns, but merely as particular indicators. However, also analyzed the collected data taking into account socio-demographic variables, such as age and time working for the company. The work presented in [12] also evaluated some driving metrics and their evolution and authors in [13] use acceleration data to establish a relationship with subjective assessments of driving style and thus be able to improve the comfort of transport users. The study of on-board comfort has also been analyzed in [14] attending to the bus lanes characteristics. However, most related work focuses on detecting some specific metrics, but not efficient or safe driving behaviors, as we propose with our driving patterns. Liu et al. [15] go further, proposing a method to extract driving patterns but also visualizing them on a color map. Finally, authors in [16] proposed an algorithm using fuzzy logic to classify drivers according to their driving style, but the experiments are in an initial stage. Detection of aggressive driving styles has also been studied in [17], where data collected from the accelerometer and gyroscope of a smartphone is used. In this sense, mobile phones have proven effective in measuring and recording movement [18].

Other considerations are based on the type of efficient driving programs and learning process: the use of feedback devices (including mobile apps [19]) or training sessions are different approaches to change driver behavior. There are different studies in the literature comparing both techniques. Roy et al. [20] conclude that, although the attitude of drivers is positive, there are other factors that restrict the change in driving habits: weather or even timetables could affect the motivation to acquire new driving habits. Also, the subjective workload related to the formative actions has also been analyzed [21] with the aim of avoiding the rejection of training programs. It must not be forgotten that the driving process has a strong human component and it may be influenced by certain socio-demographic variables.

Therefore, we observe that different proposals throughout the literature have addressed different problems in the analysis and evaluation of efficient and safe driving: from the definition of metrics or driving patterns, their analysis and representation in maps, or even studies that underline the importance of the formative actions and the context in the driving performance. However, a detailed analysis with a large amount of real-time driving data, bringing together all these issues in a single infrastructure as proposed in this paper, has not been found.

Our previous work used driving patterns as a basis to evaluate driving efficiency and safety behavior. Driving patterns identify all the actions during the driving process, from the way in which the driver starts the movement of the vehicle, the movement and the finalization of the movement (the stop). From the analysis of this information, our system can obtain a numerical evaluation (from 1 to 10), associated with the level of maturity in efficiency and safe driving, by means of fuzzy logic techniques [6]. Unlike other proposals, our method of analysis and evaluation of driving behavior identifies which aspects of efficiency and safety should be improved by drivers. In addition, our system takes into account different contextual variables such as geographical, temporal or even weather conditions. Our previous work also analyzed the influence of socio-demographic information, but from a driving pattern perspective, considering driving efficiency and safety [22].

Therefore, driving behavior analysis based on driving patterns is more complex, both in terms of design and computational costs. However, the results provide detailed conclusions about the correct application of the efficient and safe driving recommendations, isolating the external factors that are outside the driver's control. In this way, the problems derived from the use of simple metrics are solved [5].

In addition, our system gathers a great quantity of detailed information, which can be applied to other applications, such as enhanced operational decisions. For instance, the driving performance of professional drivers could be associated to other factors related to the operational management of the fleet. Fleet management is a relevant activity both at an operational and tactical level [23]. Typical problems, such as cost efficiency, and new management aspects, such as safety and ecology [24], have been approached by mathematical models. We can also find proposals that take into account many factors in the decision making process, taking into consideration sustainability, where the authors identify if there has been a change in the driving style of drivers during the pandemic [25], [26], costs and emissions to determine bus frequency during rush hours [27], the influence of passenger load [28] or the passenger waiting times and bus delays [29].

Nevertheless, ITS technologies open new opportunities to improve fleet management decisions [30], [31]. In this sense, including IoT, and a complete ITS architecture as proposed in this article, new off-line variables could be incorporated into the decision-making process and could also help to improve road safety. For instance, the distribution of work shifts or changes in the assignments of vehicles or bus lines can be a key factor that penalizes the concentration and performance of the drivers. In fact, professional drivers must maintain efficient and safe behaviors throughout the entire working day. Different studies analyze the relationship between professional drivers' work shifts and their fatigue, both in terms of mental and physical fatigue [32], [33]. However, in urban public transport companies, the influence of the staff allocation with bus lines should be assessed. This analysis has not been performed in detail in the literature.

In this paper, we have analyzed different types of management strategies for urban public transport companies, taking into account the number of bus lines assigned to each driver. In each fleet, the different bus lines follow different routes. For that reason, the impact of assigning more or a smaller number of bus lines to each driver must be evaluated. The analysis is based on the adoption of efficient and safe driving techniques during working hours. The influence of such management decisions in a driving context has not been previously addressed by other works. From the large amount of analyzed data, we have shown that the number of bus lines assigned to each driver can influence not only the efficiency results in some cases, but also the anticipation and safety behavior in other cases.

III. Materials And Methods

The characterization of driver behavior using real-time driving data is possible due to on-board devices. We use the hardware and system architecture described in [4] and [34] in order to gather real-time driving data. This architecture is part of a complex framework, as shown in Figure 2. The proposed framework includes different sources of data, different SQL databases to store the raw samples and a set of developed tools to perform the analysis of the driving behavior.

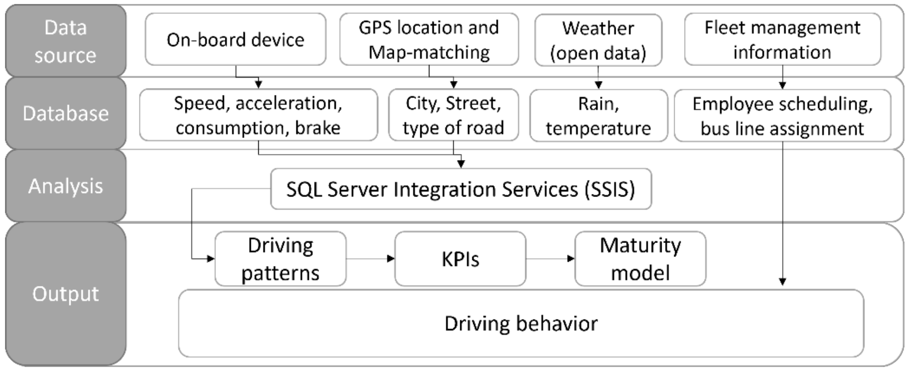


Fig. 2. Framework for driving behavior analysis.

The proposed framework includes the following information as input data ("*Data source*" in Figure 2):

- An on-board device (OBD) is installed in the vehicles and collects information from the Engine Control Unit (ECU). The OBD gathers information related to speed, acceleration, consumption and braking at 0.6 Hz. In addition, the on-board device shows real-time recommendations, as our previous work demonstrated that feedback can encourage drivers to improve their driving performance [35];
- GPS coordinates and additional modules to improve GPS locations (map-matching);
- Weather information from AEMET[1] open data sources;
- Fleet management information.

All the information from the different data sources will be stored in an SQL database. In addition, the raw samples from the OBD ("*On-board device*" in Figure 2) will be combined with GPS coordinates. A reverse geocoding module is implemented in order to store nominal information for cities, streets and types of roads. This information is also stored in an SQL database and will be useful for fleet management to locate specific areas in which driving performance is not as expected. Weather information is stored as a summary of rain events and temperatures for each day. Finally, drivers are associated with the bus-line in each of the complete routes ("*Employee scheduling, bus line assignment*" in Figure 2).

The analysis is performed using a set of developed tools using SQL server integration service (SSIS) processes. With our approach, raw driving data is filtered and transformed into driving patterns associated to safe and efficient behaviors while driving. Each obtained pattern is stored with a unique identifier. In this sense, the output information obtained accurately describes the driving behavior, independent of other external factors, such as the type of vehicle or the route. In order to complete the evaluation, driving patterns are presented in terms of KPIs and a maturity model module will obtain the overall performance.

In this paper, we have included fleet management information to analyze the influence of strategy decisions on driving behavior. The following sections will describe the phases of the experimental study and evaluation.

A. Phase 1: Data Collection

The analysis and evaluation methodology described in Section III is implemented and tested in 16 professional fleets. For this study, we have selected four fleets of urban public transport companies. The fleets have been selected taking into account the following criteria: we have chosen fleets with a high number of drivers in order to obtain statistically relevant results. In addition, the selected fleets present different approaches regarding the decisions of assigning lines to each driver.

Table I summarizes the main characteristics of each fleet according to the aim of the study. In order to maintain the privacy of the transport companies, we have named the fleets with a numerical nomenclature. However, note that three of the fleets correspond to urban transport companies in Spain and a fourth fleet is located in Morocco.

TABLE I
CHARACTERIZATION OF THE FLEETS

	Total number of drivers	**Total number of bus lines**
Fleet #1	51	25
Fleet #2	253	43
Fleet #3	83	22
Fleet #4	358	26

745 professional drivers were evaluated under the proposed framework for 10 months (from January to October 2018). All the participants are aware of the data collection process and have received the same training in efficient and safe driving. The collected data registered a total number of 6,517,983.995 kilometers in our dataset. Moreover, the samples from which the driving patterns are calculated are collected every 1.5

[1] https://opendata.aemet.es/

seconds. As a result, during a complete working day, millions of samples are collected and analyzed to extract the driving patterns. Therefore, the results presented in this work represent a valuable source of information and conclusions not previously seen for the urban transport sector.

B. Phase 2: Analysis of driving performance

In our previous work [6], we detailed the design and implementation of the driving patterns. Our driving patterns characterize efficient and safe driving behavior taking into account the influence of the driving context. In addition, our framework allows to cross the evaluation with other contextual information, such as the time of the day, streets or even the weather conditions. The characterization of the behavior during the starting, movement and stopping of the vehicle allows to extract detailed information of all the efficient, inefficient or unsafe situations that can occur during the driving process. Furthermore, we have employed fuzzy logic techniques and adapted the maturity model concept to the driving environment. Thus, we have managed to express the level of driver efficiency in numerical terms (from 1 to 10), as an evaluation [6]. Among the different patterns in [6], we have selected the following indicators to characterize the overall performance of the drivers:

- **Inertia**: it is described as when the vehicle is moving without fuel consumption;
- **Idle**: it is described as when the engine is running but the vehicle is stationary;
- **Acceleration-brake (AB)**: this pattern is detected when the driver uses the brake after a long period of continuous acceleration. It detects situations in which the driver does not foresee the driving conditions;
- **Brake-acceleration (BA)**: this pattern is detected when the driver brakes with a high-intensity level followed by the acceleration of the vehicle. It detects situations in which the driver does not maintain the safety distance.

The first two indicators are more related with efficient driving recommendations while the AB pattern refers to anticipation in driving and the BA pattern is related to safety. In order to evaluate the driving performance, besides the maturity level, we have included the analysis of the KPIs for each pattern. The KPI for the inertia (and idle) pattern is expressed in terms of time percentage in inertia (or idle) in relation to the total time. For the AB and BA patterns, the KPI defines the number of times the pattern appears every 100 km. For idle, AB and BA patterns, the lower the KPI better is the driving performance. On the contrary, the inertia pattern conveys better results with higher values of the KPI.

C. Phase 3: Statistical analysis

Based on the results of the driving performance, we have carried out several statistical analyses and added information related to decisions on the fleet management strategy. We have used IBM SPSS Statistics 24 in order to accomplish the analysis. An initial assessment of the normality of data determined that our samples do not follow a normal distribution. We have used the Kruskal-Wallis test, with a significance level of $p<0.05$, to ascertain if there are significant differences between the groups. A Mann Whitney test was used in order to ascertain which groups show significant differences, with a significance level of $p<0.05$.

With the aim of finding conclusive results, we have divided the analysis into two main groups: in an initial approach, we have grouped the data according to which fleet they belong. In the second, we have analyzed the data taking into account the number of bus lines assigned to each individual driver.

IV. Results

The general purpose of this study is to carry out a detailed analysis of the driving performance of professional drivers based on the total number of bus lines assigned to them. To characterize the strategy of the fleet managers, we have classified drivers into four groups according to the number of bus lines assigned: those who drive on less than 5 bus lines, between 5 and 10 lines, between 10 and 15 lines and, finally, with more than 15 bus lines. According to this classification, the drivers of each fleet are distributed as presented in Table II.

In order to envisage the characteristics of each fleet based on this classification, we show the results graphically in Figure 3. As shown, Fleet #2 and #3 have opposed behaviors: the former has more drivers with fewer lines assigned and the latter chooses high turnover among several lines. Fleet #1 and Fleet #4 have a more uniform allocation policy, distributing drivers in almost all categories.

TABLE II
DISTRIBUTION OF DRIVERS INTO GROUPS

	Drivers with 1-5 bus lines	Drivers with 6-10 bus lines	Drivers with 11-15 bus lines	Drivers with >15 bus lines
Fleet #1	19	15	13	4
Fleet #2	179	68	6	0
Fleet #3	0	54	29	0
Fleet #4	124	114	74	46

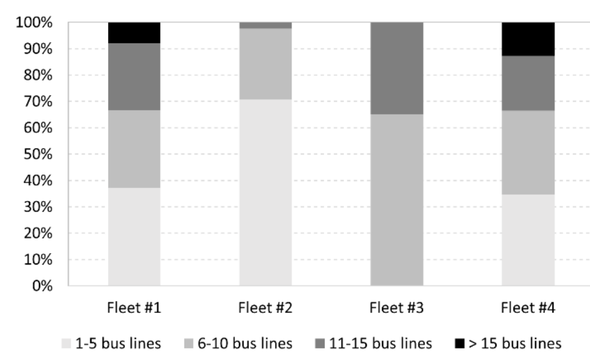


Fig. 3. Characterization of the fleet management strategies.

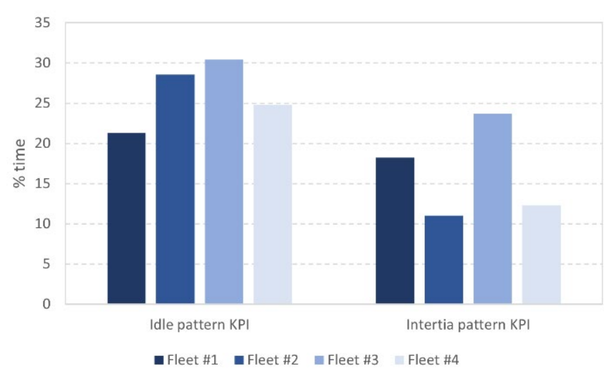
A. Evaluation of the KPIs for each fleet

Based on the characterization of the fleets, we have analyzed the KPI values for each pattern. Figure 4 summarizes the obtained results. Figure 4.a shows the idle and inertia pattern for each fleet in terms of % time of duration of the pattern among the complete routes. Figure 4.b shows the KPI values for the AB and BA patterns, expressed in the total number of events/100Km, as explained previously. Except for the inertia pattern, better results are achieved with lower values of the KPI. In addition, a complete statistical parameter description is shown in Table III, including mean and standard deviation but also confidence intervals. Comparing all the fleets, Figures 4a and 4b show that Fleet #1 and Fleet #4 have similar values in almost all the patterns. However, Fleet #2 and Fleet #3 have a different behavior, with Fleet #2 showing the worst results both for inertia (less use) and for the AB and BA patterns (higher values). As previously explained, Fleet #2 was characterized by a more conservative strategy of allocation of lines to drivers (drivers with few bus lines, as shown in Figure 3). However, the results are worse. Based on these preliminary results, it seems that drivers with fewer bus lines show overconfidence, paying less attention to the driving context and, therefore, obtain lower performance level in anticipative and safety patterns. Furthermore, the inertia pattern is also affected, possibly by drivers who have more lines (up to 10) and therefore do not have a good command of all the routes. These preliminary conclusions will be confirmed in subsequent analysis.

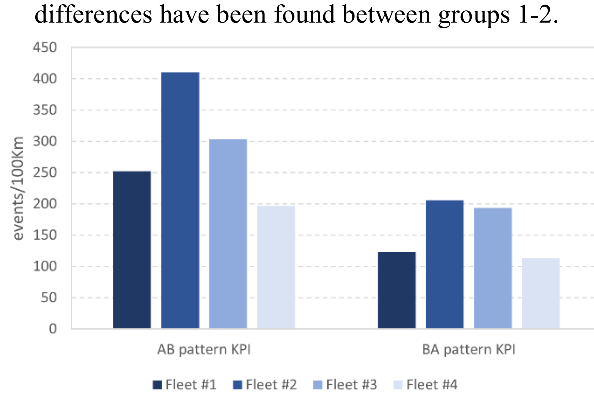
The Kruskall-Wallis test confirms the presence of significant differences between the fleets in terms of the KPI values for each pattern. Therefore, we performed the Mann-Whitney test between pairs and it has been found that, for all patterns, there are significant differences between fleets except for the idle pattern of Fleet #2 and Fleet#3 (p-value=0.27).

B. Evaluation of the KPIs considering the number of bus lines

We have performed an in-depth analysis of the driving behavior taking into account the number of bus lines. We have kept the initial classification of drivers who drive between 1 and 5 different bus lines, between 6 and 10, 11 and 15 and, finally, more than 15 bus lines. A detailed description of the number of drivers in each group is shown in Table II. This analysis includes all drivers of all fleets. With our evaluation system based on driving patterns, the driving context is taken into account and, therefore, we can include drivers from different fleets in the analysis. Statistical analysis found significant differences between the groups. Table IV summarizes the pairs in which significant and no significant differences have been found. With the aim of clearly showing the information in the Table, we have renamed drivers who drive between 1 and 5 bus lines as "Group 1"; between 6 and 10 as "Group 2"; between 11 and 15 as "Group 3" and "Group 4" includes drivers with more than 15 bus lines. As shown, there are significant differences between the groups in almost all the patterns. The exceptions are: for the idle pattern there are no significant differences between groups 1-2 and 3-4; for the inertia pattern there are no significant differences between groups 2-3; for the AB and BA patterns (anticipative and safety related patterns) no significant differences have been found between groups 1-2.



a) Idle and inertia pattern



b) AB and BA pattern

Fig. 4. KPI values for driving patterns.

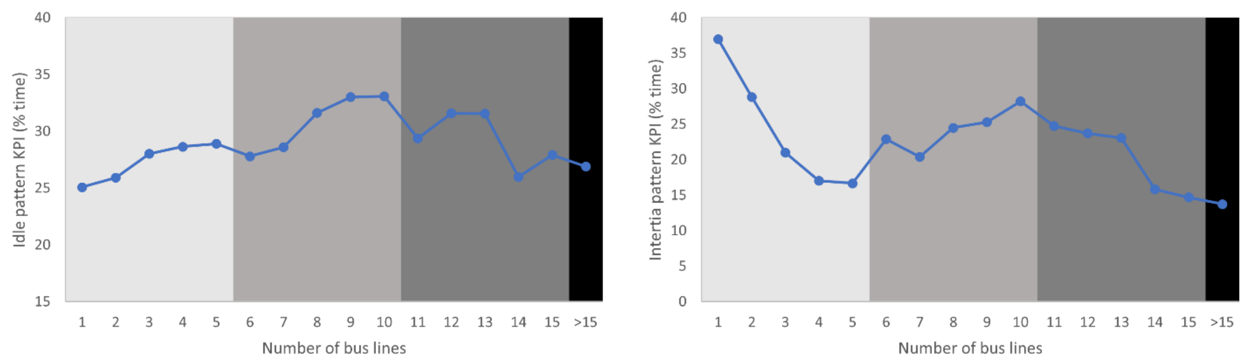
TABLE III

STATISTICAL VALUES OF DRIVING PATTERNS (MEAN ± STANDARD DEVIATION [CONFIDENCE INTERVAL 1 – CONFIDENCE INTERVAL 2])

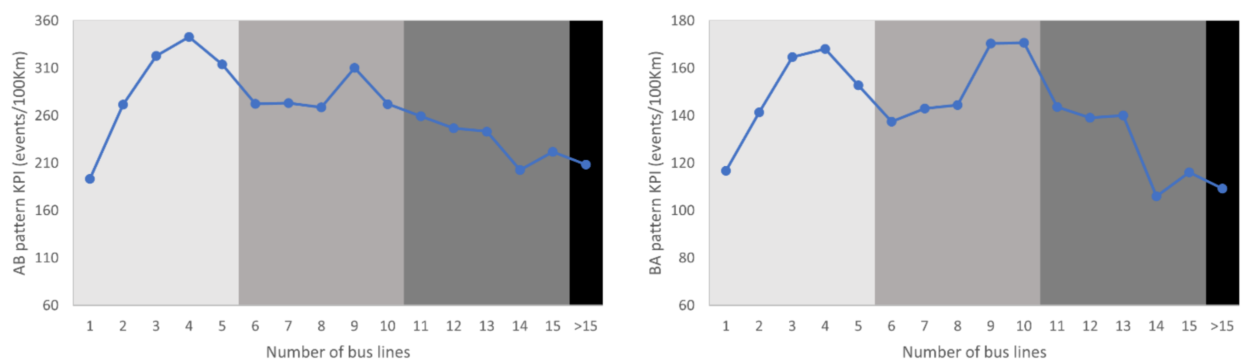
	Fleet			
	#1	**#2**	**#3**	**#4**
Idle pattern KPI	21,32 ± 3,83 [20,92 – 21,72]	28,56 ± 4,42 [28,25– 28,86]	30,45 ± 9,10 [29,68 – 31,22]	24,81 ± 6,68 [24,51 – 25,12]
Inertia pattern KPI	18,23 ± 5,7 [17,61 – 18,86]	11,03 ± 2,11 [10,89– 11,18]	23,70 ± 10,75 [22,54 – 24,87]	12,31 ± 7,60 [11,92 – 12,69]
AB pattern KPI	252,03 ± 53,91 [246,34–257,72]	410,14 ± 64,73 [404,99 – 415,28]	303,66 ± 57,02 [299.07 – 308.24]	196,37 ± 56,92 [193.78 – 198.96]
BA pattern KPI	122,81 ± 39,67 [118,58 – 127,04]	206,02 ± 52,2 [202,38 – 209,66]	193,69 ± 64,3 [188,51 – 198,86]	113,27 ± 40,29 [111,35 – 115,18]

TABLE IV
SIGNIFICANCE DIFFERENCE RESULTS

Pattern →	**Idle**	**Inertia**	**AB**	**BA**
Test →		**Mann-Whitney**		
Group 1 – Group 2	No sig. diff (p=0.59)	Sig. diff (p<0.05)	No sig. diff (p=0.60)	No sig. diff (p=0.84)
Group 1 – Group 3	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)
Group 1 – Group 4	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)
Group 2 – Group 3	Sig. diff (p<0.05)	No sig. diff (p=0.49)	Sig. diff (p<0.05)	Sig. diff (p<0.05)
Group 2 – Group 4	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)
Group 3 – Group 4	No sig. diff (p=0.57)	Sig. diff (p<0.05)	Sig. diff (p<0.05)	Sig. diff (p<0.05)



a) Idle pattern **b)** Inertia pattern
Fig. 5. Influence of the number of bus lines on efficient driving patterns.



a) AB pattern **b)** BA pattern
Fig. 6. Influence of the number of bus lines on anticipative and safety driving patterns

The evaluation of the influence of the number of bus lines on driving performance is shown in Figures 5 and 6. In general terms, for all drivers, the fewer the bus lines, the better the results in driving patterns. It should be noted that the tendency seems to revert in the AB and BA patterns, where drivers with a high number of bus lines show driving behaviors similar to drivers with fewer lines. Due to the lack of knowledge of the routes, drivers tend to show safer behaviors while driving.

C. Influence of the number of bus lines on the evolution of driving behavior

Another question to assess is the evolution of drivers over several months in the use of new techniques for safe and efficient driving. The aim of this analysis is to answer the following question: Does high rotation between different bus lines influence the application of new driving habits over time? As previously explained, for this purpose we have analyzed all the drivers of all the fleets classified, based on the number of bus lines. The results are shown in Figures 7 to 10.

Figure 7 shows the results for the idle pattern. The evolution throughout the analyzed period shows that drivers tend to revert to their original habits in this pattern. However, this behavior is more noticeable regarding drivers who have more than 5 bus lines assigned. On the contrary, for those extreme cases with more than 15 bus lines, the behavior is similar to those with fewer lines. In the light of the results, we can conclude that this is another indicator where drivers show more attention when exposed to different routes on a daily basis.

The results for the inertia pattern are shown in Figure 8. With regard to inertia, the influence of the number of bus lines is clear: in general terms, all drivers show an initial improvement. After that, the use of inertia gets worse and finally the drivers stabilize their values. However, the fewer the bus lines, the better the use of inertia over time. This behavior is indicative of the relation between the domain of inertia and the characteristics of the route: drivers who regularly drive on the same route can easily detect the areas of the route in which inertia should be used.

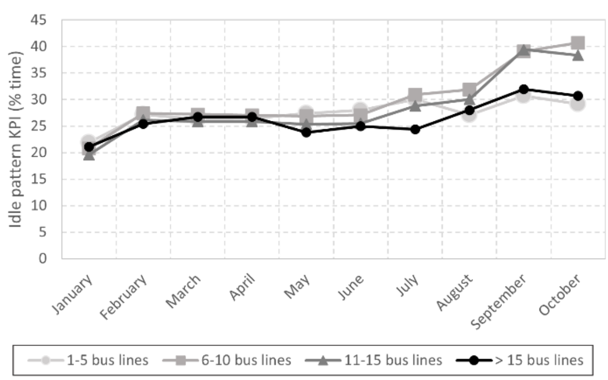


Fig. 7. Evolution of the idle pattern.

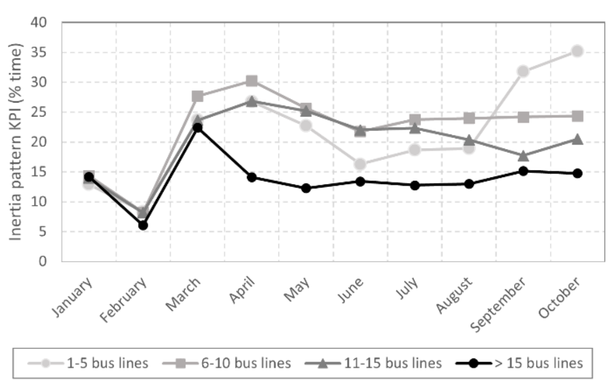


Fig. 8. Evolution of the inertia pattern.

The results of the evolution for the AB pattern are shown in Figure 9. In this case, the trend is reversed: in general terms, better results are obtained for drivers with more bus lines assigned. After the first months, there is a clear decrease in the KPI of this pattern for all groups. However, the worst results are in the group with fewer bus lines assigned. As previously explained, this pattern is related with anticipation while driving. Therefore, our results indicate that drivers who regularly drive on the same route pay less attention to the driving context. As a consequence, these drivers do not respond adequately to anticipation behavior while driving.

Finally, results for the BA pattern are shown in Figure 10. The BA pattern is related with the safety distance and the general behavior is the same as for the AB pattern. In the initial months there is a period of adaptation and learning. After that, there is a gradual decrease in the KPI value, which indicates an improvement in the pattern. However, drivers with fewer bus lines show worse results than the rest of the groups.

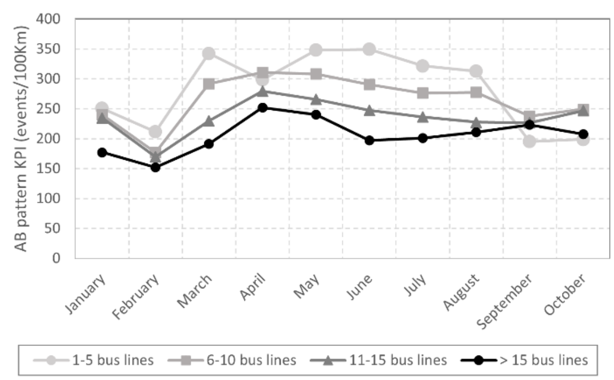


Fig. 9. Evolution of the AB pattern.

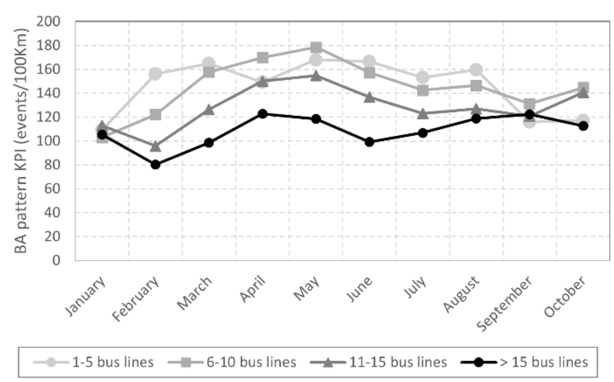


Fig. 10. Evolution of the BA pattern.

D. Influence of the number of bus lines on the maturity level

We have also analyzed the results of the maturity level of the drivers based on the number of bus lines assigned.

The maturity level allows the driver's behavior to be expressed in numerical terms, as an evaluation. In our analytical system, we have developed a method based on fuzzy logic to identify driving efficiency in linguistic terms (very high, high, intermediate or low) based on empirical data from KPIs. Thus, we obtain linguistic results in different driving circumstances: at the start of the movement, during movement or when stopping the vehicle. Finally, we calculate the maturity level based on the results of these three dimensions and assign a numerical value to said results. The details of the implementation of this maturity model are described in [6].

Figure 11 shows that the overall performance of the driver is better with fewer assigned lines. For drivers with more than 13 bus lines, the results are also acceptable. The lowest results in terms of maturity are found in drivers with an average number of bus lines between 6 and 11, with the worst data corresponding to drivers with 8 different bus lines.

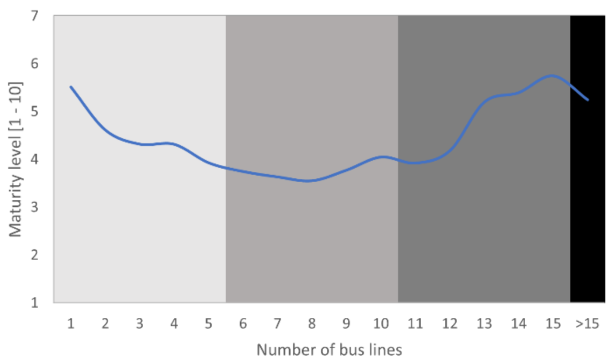


Fig. 11. Influence of the number of bus lines on the maturity level.

E. Overall evolution of driving behavior

Finally, the results of the driving behavior of each fleet are shown individually. We have analyzed the percentage of variation of the KPIs of the patterns over the months. Figure 12 includes the results of the mean variation between the months for each pattern. The background in red indicates a negative evolution on the driving pattern, while green indicates a positive variation of the overall performance over the period of 10 months.

As shown, driving performance on efficient driving related patterns (idle and inertia) presents a negative variation (except for the idle pattern of Fleet #1). This infers that drivers are more reluctant to apply the new efficient behaviors and tend to revert to their original habits. Fleet #3 shows the worst results for both patterns.

Regarding anticipative and safety patterns (AB and BA respectively), only the results of Fleet #4 worsen. Fleet #3, as opposed to efficient driving patterns, shows the best results in incorporating the anticipative and safety recommendations.

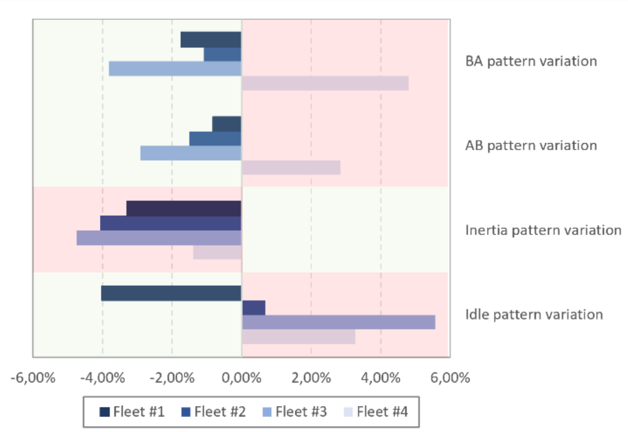


Fig. 12. Overall evolution throughout the months.

V. Discussion

We have performed different statistical analysis with the aim of establishing the influence on the driving patterns of the number of bus lines assigned to each driver. The analyzed driving patterns correspond to efficient driving patterns (idle and inertia), anticipative pattern (AB pattern) and safety pattern (BA).

To perform the evaluation, we have chosen four urban public transport companies. A baseline of 10 months is selected in order to gather real-time driving data for 745 professional drivers. The driving pattern evaluation is integrated in a complex architecture including on-board devices, database storages and the integration of different data sources. This is complemented with off-line analysis using SSIS processes in order to extract driving patterns and KPIs.

According to the total number of bus lines assigned to each driver, we have created four groups: fewer than 5 lines, between 6 and 10, between 11 and 15 and more than 15 lines. With this classification, we have found that the fleet management policy for Fleet #1 and Fleet #4 distributes drivers among all groups. Fleet #2 is characterized by the predominance of drivers with fewer bus lines, while Fleet #3 is formed, principally, by drivers with a medium/high concentration of bus lines.

With these basic differences, we have found that Fleet #1 and Fleet #4 have similar results in terms of mean values of the KPIs for all patterns. Fleet #2 has the worst results on three of the four analyzed patterns, including inertia, AB and BA. Therefore, contrary to what might be expected, worse results are obtained in fleets with a policy of more restrained bus line assignment. This indicates that drivers have deeply entrenched driving habits in their usual routes and the change in driving behavior is less noticeable.

We have also verified that idle and inertia patterns are the driving behaviors which drivers appear more reluctant to incorporate. The same does not happen with anticipative and safety patterns (except for Fleet #4).

KPI values were also analyzed taking into account the total number of bus lines of each driver. For idle pattern KPI, results worsen with the increase of bus lines per driver. However, drivers with a high number of bus lines in their work shift show similar values to those with fewer bus lines. The inertia pattern shows clear deterioration within each group (less than 5 lines, between 6 and 10, between 11 and 15 and more than 15) with the increase of bus lines. Nevertheless, an exception has been found in the group between 6 and 10 bus lines, in which the tendency is inverted (the more bus lines, the better the results). AB and BA patterns show similar behaviors, that is, a deterioration in each group when the number of bus lines is incremented, except for the group of 11-15 bus lines. This indicates higher than average levels of fatigue in professional drivers and that this has an impact on their driving behaviour. Similar results observed in [36] suggest that high levels of fatigue that drivers are prone to develop during their working hours, could be an important issue to address through occupational health strategies. The results are in line with those obtained in other studies with similar research domain [37].

The evolution over the 10 months has also been analyzed. It has been proven that the idle pattern shows increasing values throughout the month period in all groups. The inertia pattern tends to improve in the initial months, but with stable values after that. The group with fewer bus lines shows a slight improvement in the last months. It is noticeable that the groups with more assigned lines have worst results regarding inertia. This is a clear indication of the relationship between the domain of the inertia pattern and the knowledge of the bus route. For the AB and BA patterns, the evolution is more contained over time.

Finally, we have analyzed the maturity level of the drivers. The maturity level computation involves more complex driving patterns. In this sense, results are insightful: driving performance worsens with an increased number of bus lines. However, drivers with more than twelve lines show results analogous to drivers with fewer bus lines. Therefore, drivers who drive on routes sporadically also obtain good driving performance results as they pay more attention to the driving context.

VI. Conclusions

In this paper we have carried out a comprehensive analysis of real-time driving data using a large number of samples. We have also integrated fleet management information into a complex analytic system. This has allowed us to draw conclusions that, otherwise, would not have been easily observed.

In the light of the results, we can conclude that the fleet management strategy based on reducing the number of bus lines for each driver is the best policy to achieve satisfactory results in terms of driving performance, but not so much in terms of anticipation and security. However, the decisions based on a moderate number of bus lines per driver could accomplish better results in anticipative and safe driving patterns. This is due to paying greater attention while driving due to not knowing the routes in detail. Thus, attending to the fleet management strategy, reinforcement driving courses should be incorporated, focused on the use of inertia, (with a moderate number of bus lines per driver) or focused on anticipative and safe driving (with fewer bus lines per driver).

Therefore, the fleet management sector can benefit from the results of this study, not previously addressed by any other work. In this sense, urban transport companies could also carry out an analogous analysis such as that presented in this paper. In that way, they will be able to verify if their management policy is aligned with the business goals.

Our future work includes the design of new complex driving patterns, including vertical accelerations and turns, and more information context, which can bring more detail to fleet management decisions. In addition, the analyses can be extended to include other management information, such as work shifts, driving experience or passenger comfort. Moreover, we can include an additional module in our framework to detect the appearance of unsafe driving patterns at specific locations in the route. The inclusion of this additional data in a dashboard, such as that presented in [6], provides evident added value in the field of fleet management. Moreover, we shall explore ways to collect data at a lower cost by using smartphones that provide good reliability in measuring and recording movement. Finally, given the fact that electric vehicles are being gradually incorporated to the fleets of transport companies, new patterns must be designed, and further studies need to be carried out.

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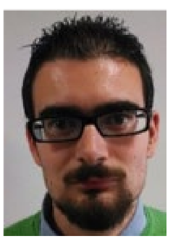
Laura Pozueco holds a MEng (Oviedo) and a PhD (Open University) in Higher Telecommunications Engineering. She is an Assistant Professor at the University of Oviedo. Her current research interests lie within the area of efficient and safe driving in combustion vehicles, edge-computer architectures, human-computer interaction devices and advanced driving assistant systems.

Nishu Gupta is a Senior Member, IEEE. He is a Postdoctoral Fellow (ERCIM Alain Bensoussan Fellowship) in the Department of Electronic Systems, Faculty of Information Technology and Electrical Engineering at Norwegian University of Science and Technology (NTNU) in Gjøvik, Norway. He is also a visiting researcher at the University of Oviedo, Gijón, Spain under the research group on Systems for Multimedia and the Internet of Things (SMIOT). His research interest includes Autonomous Vehicles, Internet of Things, Internet of Vehicles, ADAS, Vehicular Communication, Driving Efficiency and Traffic Pattern Prediction.

Xabiel G. Pañeda has a Ph.D. degree (2004) from the University of Oviedo and is currently an Associate Professor at the same university. His main research areas are the Internet of Things and edge-computer architectures. He has been working on these topics and others such as HCI and learning technologies to design advanced driving assistant systems for the last ten years.



Víctor Corcoba is an Associate Professor of the Computer Science Department at the University of Oviedo (Spain). In the past, he was a postdoctoral researcher for Telematic Engineering at the University Carlos III in Madrid (Spain). He obtained a Ph.D. from the University Carlos III (Spain) and after obtained an MSc at the University of Granada (Spain). He is working on wearable devices, stress detection, and intelligent systems for improving driving safety and fuel consumption. He has more than nine years of experience working in research projects related to intelligent transportation systems. He is the author of four books, and more than 40 articles on energy efficiency and safety in vehicles.

David Melendi is a Computer Science Engineer with a PhD from the University of Oviedo, with an interest in multimedia systems, human computer interaction, efficient driving, ad hoc networks and intelligent transportation systems. He is an Associate Professor at the University of Oviedo. He is currently working on systems for efficient and safe driving in combustion vehicles, edge-computer architectures, human-computer interaction devices and advanced driving assistant systems.

Roberto García is an Associate Professor of Telematic Engineering at the University of Oviedo (Spain). In the past, he was an Associate Professor for Electronic Technology at the University of Alcala (Spain). He obtained a Ph.D. from the University of Oviedo after he obtained an MSc in Telecommunications at the Polytechnical University of Madrid (Spain). He is currently working on systems for efficient and safe driving in combustion vehicles, edge-computer architectures, human-computer interaction devices and advanced driving assistant systems.

Abel Rionda, received the M.Sc. degree in computer engineering from University of Oviedo and the Ph.D. degree from UNED. He is currently the CEO with ADN Mobile Solutions and ecodriving platform Bledsystem. His research interests are efficient driving and embedded systems.