# Understanding Factors Affecting Fuel Consumption of Vehicles Through Explainable AI: A Use Case With Explainable Boosting Machines

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A significant economic cost for many companies that operate with fleets of vehicles is related to their fuel consumption. This consumption can be reduced by acting over some aspects, such as the driving behaviour style of vehicle drivers. Improving driving behaviour (and other features) can save fuel on a fleet of vehicles without needing to change other aspects, such as the planned routes or stops. This is important not only for mitigating economic costs within a company, but also for reducing the emissions associated to fuel consumption, mainly when the vehicles have petrol or diesel engines.

In this paper we show how Explainable Artificial Intelligence (XAI) can be useful for quantifying the impact that different feature groups have on the fuel consumption of a particular fleet. For that, we use Explainable Boosting Machines (EBM) that are trained over different features (up to 70) in order to first model the relationship between them and the fuel consumption, and then explain it. With it, we compare the explanations provided by the EBM with general references from the literature that estimate the poten-

tial impact that those features may have on the fuel consumption, in order to validate this approach.

We work with several real-world industry datasets that represent different types of fleets, from ones that have passenger cars to others that include heavy-duty vehicles such as trucks.

## 1 | INTRODUCTION

Reducing fuel consumption within a fleet of vehicles from a company is critical, since it has impacts on several aspects, such as the economic costs, and for fuels such as petrol and diesel, it also has an impact on emissions. For example, for a company operating in Spain with 100 diesel vehicles that have an average fuel consumption per vehicle and month of 30 liters, the economic cost will be 3930 Euros, taxes included (considering the average price per liter of petrol in Spain: 0.609 Euros, without taxes; 1.31 Euros after taxes as of March 2021 [1]).

Together with that, it also has an environmental impact in terms of emissions (e.g. CO2) principally for diesel and petrol vehicles. Just in Spain, the average monthly fuel consumption for the automation sector (only diesel) is around 1.8M T (in December 2020) [2]. Considering an estimate of 2.67633 Kg of CO2 per liter of diesel [3], this translates into 4.82M T of C02 emissions each month. It is true that these emissions will be reduced by the transition to hybrid and electric vehicles. However, in US, by 2030, it is estimated that only the 7% of the vehicles will be electric [4]. This highlights the need for finding complementary solutions in the meantime that help reducing vehicle emissions while they are progressively changed into electric ones.

The reduction of both economic costs and emissions is achievable by optimizing the fuel consumption of the individual vehicles of a fleet. This is something that, according to the literature, can be done by operating over different aspects that affect the fuel consumed by a vehicle during a route. For instance, [5] indicates how the impact on fuel consumption by aggressive driving can be around the 26% of the total fuel consumed by a vehicle. This means that simply optimizing the driving style of the drivers of a fleet has a significant direct impact on both the economic costs and emissions reduction.

The literature analysis on the variables that impact fuel consumption is useful in itself. However, it can be complemented using techniques that can automatically explain for an individual fleet what actionable features are impacting fuel consumption, and how much. This could be helpful for quantifying the potential economic saving and emissions reduction for that particular fleet. A set of techniques that answer this problem are Explainable Artificial Intelligence (XAI) algorithms.

Before XAI, there was a dichotomy on whether to use whitebox algorithms or blackbox ones to solve AI-related problems. Whitebox algorithms can directly explain the relationship between input and output features, in exchange of potential limitations on the modelling between those input and output features. For instance, a Linear Regression model is considered whitebox, but the modelling limitation is that the relationship inferred between input and output is linear. On the other hand, blackbox algorithms can potentially infer better relationships between input and output

(e.g. by inferring non-linear relationships), but in exchange of not being able to provide clear explanations about those relationships. XAI came to close this bridge by discovering ways to either apply algorithms that explain the relationships in a blackbox model, or by using new whitebox algorithms that can infer complex relationships between input and output. This last case is what happens with Explainable Boosting Machines (EBM). EBM is an algorithm that provides feature relevance based explanations (similar to a Linear Regression model) that allow to see the individual impact of the input features on the output.

XAI in general, and the EBM algorithm in particular, is seen as useful within the literature to understand the relationships between a set of input features and an output one. To the best of our knowledge, it has not been studied within the field of vehicle fuel consumption. Using an algorithm such as EBM can be useful for solving the problem aforementioned: understanding the impact that different actionable features have on the fuel consumption of a particular fleet. With that, fleet managers and fleet operators can discover potential ways for reducing economic costs while looking after the environment, contributing to environmental Sustainable Development Goals (SDG), like SDG11 and SDG12 [6].

Following this, the main contributions of our work are:

- Elicit up to 70 features that may have a potential impact on fuel consumption according to the State of the Art (SOTA), and analyse over several real-world industry datasets if EBM is able to correctly model the relationship between them and the fuel consumption of a vehicle in terms of predictive power.
- Retrieve the explanations from the EBM algorithm and analyse if they are aligned with the SOTA (e.g. if the relative impact of a particular group of features is similar to what the SOTA indicates). With this, we want to assess and validate the quality of the explanations provided by the EBM algorithm and measure them from a domain knowledge perspective.
- Quantify how much extra fuel the EBM explanations are able to cover, and measure the results. First, we will detect vehicles with anomalies in the fuel consumption while detecting how much fuel could be considered anomalous, and compare that extra fuel with the extra fuel explained by the EBM algorithm. Second, we will check if the fuel consumption without that extra fuel detected by the model is aligned with the catalog fuel consumption for a vehicle from the same make, model, year, fuel type and over the same route type (city, combined or highway).

The rest of the paper is organized as follows. First, we describe the related work in the area of factors that impact in the fuel consumption, together with previous works regarding the usage of Machine Learning (ML) within the context of vehicle fuel consumption. Then, we describe our proposal, first explaining the EBM algorithm, and then explaining the variation of that algorithm that we will use along with the system architecture that we will use for generating the explanations and quantifying the impact of the different feature groups in the fuel consumption. Following this, we present an empirical evaluation using real-world industry IoT data belonging to different fleets of vehicles. We conclude, showing potential future research lines of work.

## 2 | RELATED WORK

### 2.1 | Factors for fuel consumption in a vehicle

Fuel consumption can significantly vary from one vehicle to another, even when comparing two vehicles from the same make, model, year and fuel type. This is caused by different factors that may increase or decrease the amount of fuel consumed during the same trip. The literature contains many studies that identify these factors and assess

how much fuel could be saved when they are optimized. This is something very relevant for fleet managers.

[7] presents a literature review of different factors that have a potential impact in the fuel consumption of a vehicle, together with their relative importance. Figure 1 shows the categories of fuel factors considered in that review.
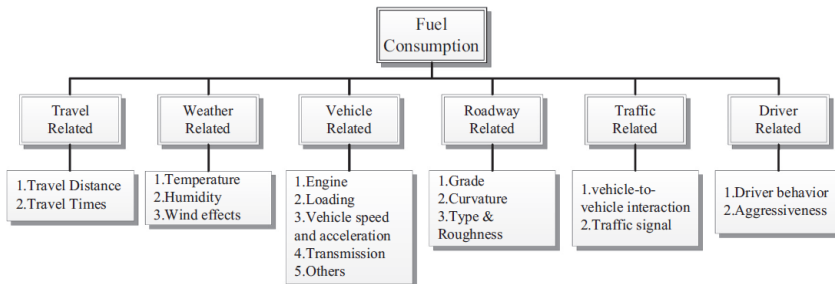


**FIGURE 1**   Categories of fuel factors discussed in [7]

The first category considered are **travel-related** factors. This group includes factors that are related to the route covered by the vehicle. In fact, the authors mention **eco-routing** as a crucial aspect to reduce fuel consumption. Fuel can be saved by choosing an optimal route not only in classical terms of distance and travel time, but also in terms of a route that saves fuel compared to other possible ones (e.g.choosing routes with less "bumps" or "slopes"). In fact, the new route may even be longer in time or distance, but offers fuel saving. The paper indicates that eco-routing alone can reduce the fuel consumption of a vehicle by 18% to 23%.

The second category includes **weather-related** factors. These factors impact the fuel consumption of a vehicle in an indirect way (i.e. by being related to the usage of the air conditioner, by affecting the water pump, by increasing the engine or transmission friction in a cold weather...). Thus, this category includes factors like the exterior temperature, the relative humidity or the wind effects. These factors may be responsible for about a 1% of the fuel consumption of a vehicle.

The third group of factors are named **vehicle-related**. It includes factors mainly related to the engine and the vehicle itself, such as vehicle load, vehicle speed, engine speed, type of fuel, whether the vehicle has an exhaust after-treatment system or not...

The fourth group is named **roadway-related factors**. It refers to factors related to the road condition, like the road slope, the surface roughness, or the road curvature. These factors, though not being very actionable (sometimes it is difficult to prevent them), have a large impact on the fuel consumption (around 5 to 20%).

The fifth group of factors refer to **traffic conditions**. They are very related to a good arrangement of traffic signs, such as traffic lights. They have the potentially biggest fuel impact (around 22 to 50% of the fuel consumption).

Finally, the sixth group mentioned in the review are the **driver-related** factors, like the driving behaviour or the aggressiveness of the driving. The driving profile of a particular driver (that measures aspects such as that driving aggressiveness), are calculated with vehicle information such as the RPM (engine speed; revolutions per minute), the speed or the acceleration. The authors mention how aggressive driving can be responsible for up to 40% of the fuel consumption of a vehicle when compared to a calmer driving style.

The aforementioned literature review is enhanced by the study of [5]. Here the authors present a thorough analysis regarding the influence of different factors for fuel consumption in a vehicle, along with the influence for CO2 emissions. This study considers passenger vehicles under real-world operating conditions. Regarding fuel consump-
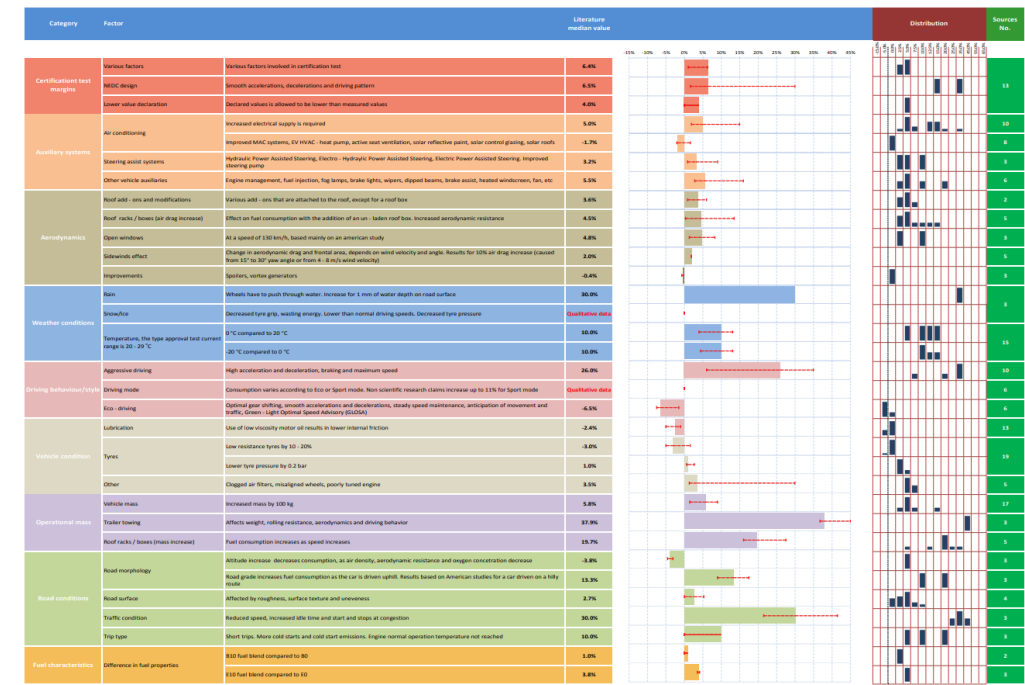
| Category | Factor | Description | Literature median value | Sources No. |
|---|---|---|---|---|
| Certification test margins | Various factors | Various factors involved in certification test | 6.4% | |
| | NEDC design | Smooth accelerations, decelerations and driving pattern | 6.5% | 13 |
| | Lower value declaration | Declared values is allowed to be lower than measured values | 4.0% | |
| Auxiliary systems | Air conditioning | Increased electrical supply is required | 5.0% | 10 |
| | | Improved MAC systems, EV HVAC - heat pump, active seat ventilation, solar reflective paint, solar control glazing, solar roofs | -1.7% | 8 |
| | Steering assist systems | Hydraulic Power Assisted Steering, Electro - Hydraulic Power Assisted Steering, Electric Power Assisted Steering, Improved steering pump | 3.2% | 3 |
| | Other vehicle auxiliaries | Engine management, fuel injection, fog lamps, brake lights, wipers, dipped beams, brake assist, heated windscreen, fan, etc | 5.5% | 6 |
| Aerodynamics | Roof add - ons and modifications | Various add - ons that are attached to the roof, except for a roof box | 3.6% | 2 |
| | Roof racks / boxes (air drag increase) | Effect on fuel consumption with the addition of an un - laden roof box. Increased aerodynamic resistance | 4.5% | 5 |
| | Open windows | At a speed of 130 km/h, based mainly on an american study | 4.8% | 3 |
| | Sidewinds effect | Change in aerodynamic drag and frontal area, depends on wind velocity and angle. Results for 10% air drag increase (caused from 15° to 30° yaw angle or from 4 - 8 m/s wind velocity) | 2.0% | 5 |
| | Improvements | Spoilers, vortex generators | -0.4% | 5 |
| Weather conditions | Rain | Wheels have to push through water. Increase for 1 mm of water depth on road surface | 30.0% | 3 |
| | Snow/ice | Decreased tyre grip, wasting energy. Lower than normal driving speeds. Decreased tyre pressure | Qualitative data | |
| | Temperature, the type approval test current range is 20 - 29 °C | 0 °C compared to 20 °C | 10.0% | 15 |
| | | -20 °C compared to 0 °C | 10.0% | |
| Driving behaviour/style | Aggressive driving | High acceleration and deceleration, braking and maximum speed | 26.0% | 10 |
| | Driving mode | Consumption varies according to Eco or Sport mode. Non scientific research claims increase up to 11% for Sport mode | Qualitative data | 6 |
| | Eco - driving | Optimal gear shifting, smooth accelerations and decelerations, steady speed maintenance, anticipation of movement and traffic, Green - Light Optimal Speed Advisory (GLOSA) | -6.5% | 6 |
| Vehicle condition | Lubrication | Use of low viscosity motor oil results in lower internal friction | -2.4% | 13 |
| | Tyres | Low resistance tyres by 10 - 20% | -3.0% | 10 |
| | | Lower tyre pressure by 0.2 bar | 1.0% | |
| | Other | Clogged air filters, misaligned wheels, poorly tuned engine | 3.5% | 5 |
| Operational mass | Vehicle mass | Increased mass by 100 kg | 5.8% | 17 |
| | Trailer towing | Affects weight, rolling resistance, aerodynamics and driving behavior | 37.9% | 3 |
| | Roof racks / boxes (mass increase) | Fuel consumption increases as speed increases | 19.7% | 5 |
| Road conditions | Road morphology | Altitude increase decreases consumption, as air density, aerodynamic resistance and oxygen concentration decrease | -3.8% | 3 |
| | | Road grade increases fuel consumption as the car is driven uphill. Results based on American studies for a car driven on a hilly route | 13.3% | 3 |
| | Road surface | Affected by roughness, surface texture and unevenness | 2.7% | 4 |
| | Traffic condition | Reduced speed, increased idle time and start and stops at congestion | 30.0% | 3 |
| | Trip type | Short trips. More cold starts and cold start emissions. Engine normal operation temperature not reached | 10.0% | 8 |
| Fuel characteristics | Difference in fuel properties | B10 fuel blend compared to B0 | 1.0% | 2 |
| | | E10 fuel blend compared to E0 | 3.8% | 3 |

**TABLE 1** Fuel factors mentioned in the literature, together with the relative importance as reported by [5]

tion specifically, the authors offer a summarized view of the literature showing different categories of variables and their proportional impact in the fuel consumption of a vehicle.

There are two approaches for analysing the impact of a specific factor in the fuel consumption of a vehicle. First, using a simulation analysis that studies the isolated impact of a factor under laboratory conditions. Second, by analysing feeds of data that contain the instant fuel consumption reported during trips on real-world environments. These feeds of data can be gathered from sources such as OBD-II (On-board diagnostics) port [8] (e.g. the Engine Fuel Rate with the PID 015E).

The analysis of the literature highlights that both approaches offer in general similar results (when there are publications available for a specific factor both from the simulation point of view, as well as with the real-world data). Thus, real-world collected data can be a valid data source for assessing the impact of different factors in the fuel consumption of a vehicle.

Here, the literature review proposes a fuel factor taxonomy that in some cases matches directly the one proposed in [7], but in some others is different. There are 28 factors than can be classified into 9 groups. All these factors, as reported by [5], appear at Table 1. This Table shows the relative importance of each of the factors (literature median value) along with an interval that encloses the different values reported, considering vehicles under real-world operating conditions. It also shows how many papers talk about that particular factor, as well as the distribution of the relative values reported.

Regarding driver-related factors, Table 1 shows a group called **driving behaviour/style** that accounts for factors related directly to the driver. It is almost similar to the one from 1 with the exception of considering factors related to good driving styles that may reduce the fuel consumption.

Regarding the group **road conditions** in [7], it mainly includes the travel related, traffic related and roadway related factors.

Vehicle-related is the group with more factor's differences between both papers. Compared to [7], these factors are split into **auxiliary systems**, **vehicle conditions** and **fuel characteristics**, complemented with other groups that include factors related to the vehicle's design itself (**aerodynamics** and **operational mass**) and to **certification test margins**. In this last review, all these vehicle-related factors account for aspects related to the vehicle itself, not considering anything directly related to the driver. This is a difference when compared to the taxonomy of [7], because vehicle-related includes acceleration and speed factors.

The difference between the analyses shown in both articles are not only in terms of the taxonomy proposed to group factors, but sometimes also regarding the reported impact (i.e. exterior temperature has a median impact reported value of 10% at [5] against the 1% impact for all weather related causes reported by [7]).

Within this last taxonomy of features that affect the fuel usage of a vehicle, some of them could be considered as "actionable", thus, they could be changed in a particular vehicle; in some cases without even needing to change the vehicle's route. An example of this is the aggressive driving style. Other features are inherent to the vehicle and cannot be directly changed, like the vehicle make/model or the vehicle mass. Even within the "actionable" features, some of them cannot be easily read through OBD-II (e.g., if there are roof add-on, which affects the vehicle aerodynamics). Thus, a subset of these features that considers only the ones that are "actionable" and the ones that can be read is the one shown in Figure 2.

| Category | Subcategory | Factor | Description | Literature Median Value (%) | Lower Limit | Upper Limit |
|---|---|---|---|---|---|---|
| Auxiliary Systems | Air Conditioning | Air conditioning | Increased electrical supply required | 5 | 2.5 | 15 |
| | Steering Assist System | Steering assist systems | Increased electrical supply required | 3.2 | 1 | 10 |
| | Other Vehicle Auxiliaries | Other vehicle auxiliaries (e.g. wipers, lights on...) | Increased electrical supply required | 5.5 | 2.5 | 16 |
| Weather Conditions | Rain | Rain | Wheels have to push thorugh water; extra energy required | 30 | 0 | 30 |
| | Ambient Temperature | Temperature 0ºC (vs. 20ºC) | Increased energy for warm up. Increased air resistance. | 10 | 4 | 14 |
| | Ambient Temperature | Temperature -20ºC (vs. 0ºC) | Increased energy for warm up. Increased air resistance. | 10 | 4 | 14 |
| Driving Behavior | Aggressive Driving | Aggresive driving | Speeding, harsh turns, harsh brakes... | 26 | 6 | 35 |
| | Eco Driving | Eco-driving | Optimal gear change, use of cruise control... | -6.5 | -12 | -1 |
| Vehicle Condition | Lubrication | Lubrication (low viscosity) | Reduces fricting within the vehicle's components | -2.4 | -5 | -1 |
| | Tyres | Low tyre pressure | Friction with the road increases | 1 | 1 | 2.5 |
| | Other | Other (e.g. clogged air filters) | Impacts the mixture | 3.5 | 1 | 30 |
| Operational Mass | Vehicle Extra Mass | Vehicle mass | Increased mass by 100 Kg (e.g. extra number of passengers) | 5.8 | 1 | 12.5 |
| Road Conditions | Altitude | Altitude | Reduces air density, reduces air resistance | -3.8 | -4 | -3.6 |
| | Driving Uphill | Driving uphill | Adds extra load for the vehicle | 13.3 | 6 | 20 |
| | Road Roughness | Road roughness | E.g. road with bumps | 2.7 | 0 | 5 |
| | Traffic Condition | Traffic condition (e.g. idle time) | E.g. Traffic jams may increase the idling time | 30 | 20 | 40 |
| | Trip Type | Trip type (e.g. short trips) | The average fuel consumption in short trips is higher than in medium/long trips | 10 | 5 | 20 |

**TABLE 2** Reduced view from the factors of [5], focusing on some of the actionable variables that can be retrieved from the OBD-II. The upper and lower limits refers to the minimum and maximum SOTA values reported in the review. For Rain, the lower limit is set to zero since the review does not provide limits for that feature.

The physical reasons as to why these features impact the fuel usage are:

- **Air conditioning (A/C)**: Using A/C increases the energy supply needed, leading to an increased fuel consumption. The time using the A/C and the power needed will increase/decrease that extra energy required. This category also includes the heating systems and related features, like the vehicle's coolant.
- **Steering assist system**: These systems help driving safely and more confortable, but require additional electrical supply in exchange. An example is the usage of Electric power assisted steering (EPAS).
- **Other vehicle auxiliaries**: These features include other auxiliary elements of the vehicle that may also require an extra energy. An example is the vehicle lights usage, that require extra energy and due to that, extra fuel.
- **Rain**: Rain (and snow) impact the fuel usage in different ways. First, they affect the wheel gripping to the road surface. Also, the wheels have to push through an additional layer of water (or snow), so extra energy is required.
- **Ambient temperature**: Temperature affects tyres, motor oil viscosity, cold start engine… Extra fuel is required in low temperatures to warm up the engine. It also affects aerodynamics: increased air density and higher aerodynamics resistances.
- **Aggressive driving**: Aggressive driving is shown through different variables: acceleration patterns, gear change, harsh turns, harsh brakes, speeding… The impact on the fuel usage could be high.
- **Eco driving**: Eco driving is related to the optimal driving of a vehicle, which may reduce its fuel usage. It involves optimizing the gear shifting (related to the usage of cruise control), choosing the best possible route thanks to a navigation device…
- **Lubrication**: Overcoming of friction within the vehicle's components requires energy, and this is related to the fuel usage. If the friction is minimized thanks to an adequate lubrication, the energy required will be lower.
- **Tyres**: Tyre pressure is related to the rolling resistance coefficient (RRC). When the tyres have low pressure, the contact surface with the road increases and more energy is needed to rotate the wheel (as the friction increases).
- **Other (vehicle condition)**: Beside tyres and lubricants, there are other vehicle conditions that impact the fuel usage. For instance, if the air filters are clogged. This is something that happens mainly in old models (since fuel injection in new cars is adjusted to ensure the correct mixture). Other examples are misaligned wheels and suspension losses.
- **Vehicle extra mass**: Extra mass in a vehicle (measured, for instance, in additional 100Kg), increase the energy needed to move the vehicle. This may happen for instance when there are additional passengers in a vehicle.
- **Altitude**: In higher altitudes the air density is lower, so the air resistance that the vehicle faces while driving is also lower. This means that in higher altitudes the vehicle needs lower energy to move the same distance.
- **Driving uphill**: Driving uphill adds an extra load over the vehicle, that needs additional energy to move. By contrast, driving downhill reduces the amount of energy needed.
- **Road roughness**: For instance, if a road has many bumps, the vehicle will need additional energy to go through it.
- **Traffic condition**: Traffic condition also impacts in the fuel usage. For instance, if there are traffic jams, the idling time normally increases, leading to an increased average fuel consumption.
- **Trip type**: The trip type also impacts in the fuel usage. For instance, if the trip distance is small, the average fuel consumption will increase, since fuel is required to turn on the vehicle.

There are some additional factors that impact in the fuel consumption that the previous references did not mention. This is the case of Diesel Exhaust Fluid (DEF). DEF is an urea-based product used in after-treatment processes of the vehicle, such as Selective Catalytic Reduction (SCR). It is applied over the vehicle's exhaust stream in order to transform the NOx gas emissions into nitrogen, water and CO2, reducing the NOx emissions in the process [9]. Techniques like SCR do not only reduce the emissions of a vehicle, but also help the engine performance and may lower fuel consumption [10, 11].

The factors already mentioned are linked to passenger vehicles, but for other vehicles, such as trucks, there are additional ones to consider. This is the case of power take-off, where there is power from the engine that is taken out (e.g. with a splined drive shaft) and used in another application (e.g. for a cement mixer in a truck). This directly impacts in the mileage of a vehicle [12].

All these references show that there is a physical and empirically measured connection between the value of specific factors and the value of the fuel consumption. Thus, it is possible to use them in order to predict the value of the fuel consumption with ML models, as already shown within the literature [13, 14, 15].

## 2.2 | Machine Learning for connecting input features to vehicle fuel consumption

As we mentioned in the previous subsection, there are several features that affect the fuel consumption of a vehicle. This can be measured using as input data source the feeds of data gathered from the vehicle's movement together with Machine Learning (ML) algorithms. This is the case of [16], where the authors conduct an study over a fleet of vehicles where they assess the impact of driving behaviour in the fuel consumption. They consider features related to driving behaviour, such as the gas pedal position, the speed and speed variance, or the steering angle, and they first see how those features have significant correlations with the fuel consumption. Then, they use several clustering algorithms (Spectral clustering, KFCM, K-Means), finding different clusters based on the driver consumption profile and its relationship with those driving behaviour features.

In [15], the authors analyse the impact of other features for fuel consumption within the context of trucks. The 56 features used include characteristics from the vehicle, such as its gross weight, together with others belonging to driving behaviour (usage of cruise control, average speed...), as well as information from the road (like the road surface macrotexture, or the curvature of the road). Those input features are seen as correlated with the fuel consumption (using a bivariate correlation analysis), and then are used to train several ML models (ANN, SVM, Random Forest) in order to predict the fuel consumption of the trucks. For the case of Random Forest, the authors viewed the relative impact from the different features in the fuel consumption through their contribution for accuracy during the tree splitting process.

The previous approaches are useful for detecting dependencies between a set of features and the fuel consumption of a vehicle. However, they do not quantify exactly how many extra liters of fuel are spent due to those features. In [17], the authors investigate the impact of eco-driving in the fuel consumption. Eco-driving is expressed through several features related to variables such as the Revolutions Per Minute (RPM) or the braking. Then, they use statistical tests for detecting significant decreases in fuel consumption when an eco-routing driving style is used. Then, they use a Logistic Regression model for analysing the relationship between driver-related features and the fact that the vehicle trip was actually done with eco-routing.

It is possible to use a Linear Regression model for measuring the individual impact of input features in fuel consumption, and know exactly how many liters are used due to each individual variable. The reason behind this is that those models are known as whitebox because they directly provide the influence of the input in the output [18]. This is shown in [19], where the authors predict the fuel consumption gap between type-approval tests and real-world driving trips, using the information of one vehicle during one year, and with 20 different drivers. With that, they build a multiple linear regression model that takes into account driver-related factors as well as environmental and traffic factors in order to predict the fuel consumption gap. Through these linear models, they provide the relative importance for each of the features in the fuel consumption, as well as the r2 value for each of the models tested in order to evaluate them. Similarly, in [20] the authors study the impact on the fuel of several features inferred related to driving behaviour through the analysis of the data from two different vehicles. One of these features is the Driving Style In-

dicator (DSI), which is the difference between the average positive acceleration of a vehicle minus the average of the negative acceleration divided by the average speed. The relationship between these features and fuel consumption is modeled through linear regression algorithms in order to quantify the impact of each one of them.

Even though linear regression models can be used for fuel prediction when there is a need of a whitebox ML algorithm that explains the relationship between input and output, this limits the results since the relationship inferred is linear.

This problem can be solved by using non-linear whitebox models, such as Generative Additive Models (GAM). These models, instead of modelling the relationships between the input features and the output value though a constant coefficient, they infer individual and additive relationships through non-linear functions. This has been proved useful in other domains. In [21], authors identify risk factors and interaction effects in order to to predict intensive care admission in patients hospitalized with COVID-19. In [22], authors use GAM models to predict goals in soccer along with the quantification of the impact of the different input factors on the output. However, to the best of our knowledge, these models have not not been used for both predicting fuel consumption along with the quantification of factors that impact on it.

## 3 | METHOD

In this Section we describe the XAI whitebox algorithm considered in this work for obtaining the explanations, as well as the logic used for generating them. We also include the schema for the whole process, and the steps involved for analysing and evaluating those explanations.

### 3.1 | Explainable Boosting Machines (EBM)

EBM [23] is a type of whitebox model that provides feature-relevance based explanations. It can be used for both regression and classification tasks, and similarly to other whitebox models, such as Linear or Logistic regression algorithms, it infers an independent relationship between input features and the output variable. Because of that, it is possible to know the individual contribution from those input features for a particular output value. The advantage of EBM is that it provides the option to infer non-linear relationships, and due to that, it can potentially increase the model generalization [24]. EBM is based on the $GA^2M$ algorithm [25], but with a difference in terms of computation performance. EBM is an evolution from Generalized Additive Model algorithms (GAM) [26] because not only it is able to model individual relationships between the input features and the output, but it can also model pairwise interactions between input features, and include them as additional terms. The expression for the EBM algorithm appears in Equation 1 for the regression case. In that Equation, $\sum_{n=1} f_i(x_i)$ represents the different functions that model the individual relationship between a specific input feature $x_i$ and the output $y$ through a specific link function $g$. Similarly, $\sum_{n=1} f_{ij}(x_i, x_j)$ represents the pairwise function term that models the relationship between two input features $x_i, x_j$ and the output $g(E[y])$. Finally, $\beta_0$ represents the intercept that adjusts the prediction from the model. For the sake of simplicity in both the training and the explanations generated, we have not considered pairwise interaction terms for the analysis carried out in this paper (the hypeparameters of the model allows to choose whether or not to include them).

$$g(E[y]) = \beta_0 + \sum f_i(x_i) + \sum f_{ij}(x_i, x_j) \tag{1}$$

## 3.2 | EBM variation for vehicle subgroups

Besides the standard EBM implementation, we use the EBM variation described in both the Patent [27], as well as in [28]. In this proposal, there is a base EBM model trained in all the data, and then there are additional EBM models trained in subsets of data belonging to the different vehicle models. This is important because using only one EBM will cause that the individual contribution in the average fuel consumption for one variable (e.g. the number of jackrabbit events) will be the same regardless of the model, and this is something that may not be true. The impact could be different depending on the vehicle model, and this is something that should be taken into account when making the predictions and explaining the individual impact in the output variable. Because of that, if additional models are trained over those subsets, trying to predict the error from the base EBM, the final prediction and the final explanations could be adjusted according to those subgroups. The original proposal allows to specify any type of subgroups (which could consider other features besides the vehicle model). However, for the analysis in this paper, we will only consider the vehicle model.

## 3.3 | Explanation generation

In this Subsection we show the full process followed for obtaining the explanations and for evaluating them later. This schema appears in Figure 2.
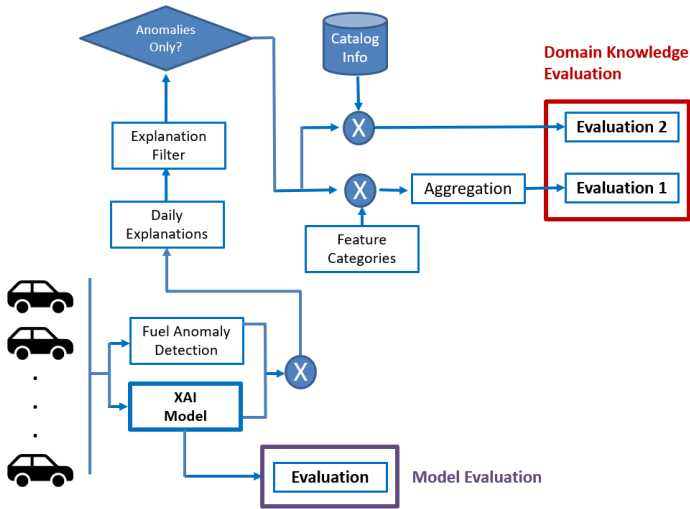


**FIGURE 2**    Schema for the process of aggregating the explanations in order to compare them with the SOTA.

Using the databases with vehicle information (described in more detail in Subsection 4.1), we both identify fuel outliers and we also train the XAI whitebox model that infers the relationship between input features and fuel consumption.

Regarding the anomaly detection step, it detects vehicles and dates where the average fuel consumption is anomalous, considering the other vehicles from the same model and for the dates that are associated to the same route type. That route type is the primary route type of a vehicle in a day (highway, city or combined). The algorithm applied is

described in Equation 2. Using the whiskers from a boxplot analysis, the vehicle-dates with anomalous fuel consumption are detected with an univariate approach considering the average fuel consumption from other vehicles from the same model and route type.

$$lim\_sup = Q3 + 1.5 \times IQR$$
$$lim\_inf = Q1 - 1.5 \times IQR$$

(2)

This approach is useful since it directly provides a fuel threshold that indicates the amount of fuel that is anomalous for a particular vehicle. In this paper we will only use the upper limit for the context of the explanations, since it is the one that identifies high fuel consumption. the An example of these limits appear in Figure 3 for one vehicle. We see that the different dates are categorized as "city", "combined", and "highway", and there is a threshold that highlights the amount of fuel that in some of those days is anomalous for that vehicle.
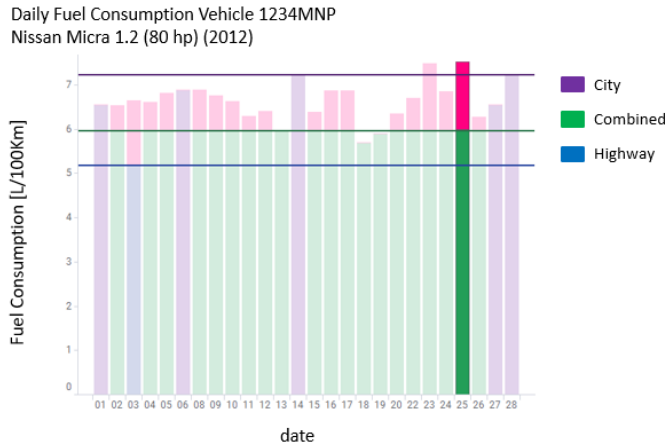


**FIGURE 3** Output example for the fuel anomaly detection for one vehicle. It shows the maximum limit for that vehicle model with respect to the three route types (city, combined, highway), highlighting the fuel part that is anomalous because is above those limits.

The information provided by the anomaly detection step will be used later on the evaluation step to analyse how much of the anomalous extra fuel is covered by the XAI explanations.

Regarding the XAI model, after training it, we get its raw explanations (Daily Explanations step). There are several combinations of vehicle-date-feature where we have the feature relevance for each feature, for each vehicle and for each date. However, since the functions that express the relationship between input features and the output are not linear, we calculates the average fuel reduction for each vehicle and each date if every one of those features changed from its actual value to a reference value (e.g. if the tyre pressure increases from its actual value to the median value that it usually has for the vehicles of the same model). An example of this appears in Figure 4.

Thus, for every vehicle-date-feature we see how the feature relevance changes when the feature value changes from the current one to another reference value. This reference value can be either zero (for features identified with "Yes" in the "Reference Zero" column in Tables 10 and 11) or the median feature value for the vehicles from the
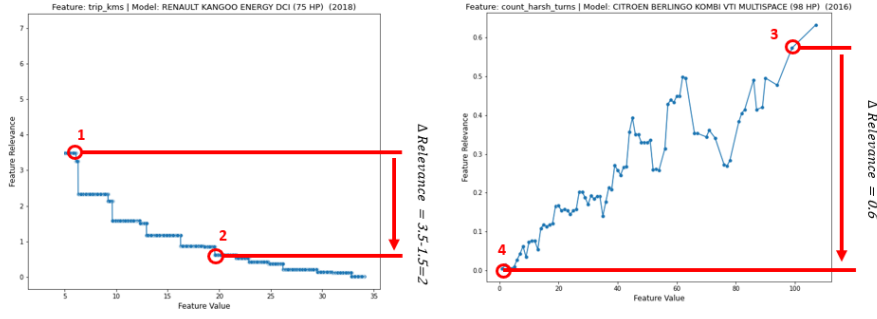
**FIGURE 4** Example of the explanation generation. The first image shows the feature relevance for trip kms, and the second one for harsh turns. The explanations for points 1 and 3 corresponds to the feature relevance difference with respect to the reference points 2 and 4 respectively.

same model that have a fuel consumption that is not anomalous (according to Equation 2). Equation 3 shows that fuel reduction for a particular vehicle, and for a feature $i$, $x(i)$ the feature value for that feature, $f_i(x(i))$ its feature relevance, for a date associated with a route r, and $m$ being the vehicle's corresponding model. The Equation also shows how the reference value $x_{ref}$ changes.

$$y_{fuel\_saved}(i) = f_i(x(i)) - f_i(x_{ref})$$

With

$$x_{ref} = Median(X[route = r, model = m, feature = i])$$

if $i$ not in 'Reference Zero'; 0 otherwise

(3)

An example of the explanation output appears in Table 3, where there is a row for each vehicle (vehicle_id), date (date_tx) and feature (e.g. the number of jackrabbit events, count_jackrabbits). The variable vehicle_group indicates the id associated to the group (make, model, year and fuel type) for that vehicle_id. route_type indicates the type of route for that specific date ("city", "combined" or "highway"). Complementing this, "avg_fuel_consumption" indicates the average fuel consumption for that vehicle in that date (L/100Km), and limit_group the threshold limit that identifies when the average fuel consumption for a particular vehicle is anomalous (L/100Km). Along with that, it includes the intercept (which can vary from vehicle group to vehicle group because of the EBM variation described in Subsection 3.2). Then, feature_relevance contains the feature relevance for that vehicle-date, and feature_value its corresponding value. target_value shows the recommended value for changing that particular feature, and following that, y_diff shows the average fuel consumption (L/100Km) that would be reduced by doing that. y_fuel_new shows the new average fuel consumption (L/100Km) that would be achieved by applying all the recommendations from the explanations in a particular day.

A final note is that since the explanations show potential fuel savings when we change a feature value to a target one, the feature reduction will be obtained in the same one regardless of whether we need to increase the feature value or decrease it (ash shown in Figure 4).

After that previous step, we apply several business rules for filtering some of the explanations generated (Explanation Filter step). These rules are:

| vehicle_id | date_tx | route_type | vehicle_group | intercept | feature | feature_relevance | feature_value | target_value | avg_fuel_consumption | limit_group | y_pred | y_diff | y_fuel_new |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| id1 | 17/04/2020 | highway | 0 | 7.25 | mean_forward_acc | 0.2087 | 2.41 | 0.48 | 9.96 | 9.35 | 10.39 | 0.22 | 8.31 |
| id1 | 17/04/2020 | highway | 0 | 7.25 | count_jackrabbit | 0.0568 | 9.0 | 0.0 | 9.96 | 9.35 | 10.39 | 0.06 | 8.31 |
| id1 | 17/04/2020 | highway | 0 | 7.25 | mean_speed_hwy | 1.0465 | 99.5 | 75.73 | 9.96 | 9.35 | 10.39 | 1.18 | 8.31 |
| id1 | 17/04/2020 | highway | 0 | 7.25 | mean_exterior_temp | 0.2581 | 282.65 | 287.9 | 9.96 | 9.35 | 10.39 | 0.07 | 8.31 |
| id1 | 17/04/2020 | highway | 0 | 7.25 | count_harsh_turns | 0.0947 | 11.0 | 0.0 | 9.96 | 9.35 | 10.39 | 0.12 | 8.31 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | count_neutral | 0.0048 | 8.0 | 0.0 | 8.3 | 7.89 | 9.07 | 0.09 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | count_jackrabbit | 0.0195 | 3.0 | 0.0 | 8.3 | 7.89 | 9.07 | 0.03 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | rpm_red | 0.0512 | 10.0 | 0.0 | 8.3 | 7.89 | 9.07 | 0.12 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | rpm_yellow | 0.1954 | 17.0 | 0.0 | 8.3 | 7.89 | 9.07 | 0.22 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | rpm_orange | 0.2774 | 30.0 | 0.0 | 8.3 | 7.89 | 9.07 | 0.36 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | count_speed_limit_90 | 0.154 | 154.0 | 17.0 | 8.3 | 7.89 | 9.07 | 0.15 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | rpm_high | 0.4663 | 179.0 | 0.0 | 8.3 | 7.89 | 9.07 | 1.48 | 6.49 |
| id56 | 30/04/2020 | combined | 14 | 7.26 | mean_side_to_side_acc | 0.0402 | 1.05 | 0.83 | 8.3 | 7.89 | 9.07 | 0.04 | 6.49 |

**TABLE 3** Example of the explanations provided by the system.

- BR1: The features used for training the model may be numeric (e.g. time driving uphill) or categorical (e.g. the vehicle model). All those categorical features are one-hot encoded before training the model. However, they are not considered for the explanations since they are not actionable.
- BR2: We remove the features in the vehicle-date explanations that have a very low impact on the fuel consumption (relative impact below 1%)
- BR3: The explanations only include vehicles where the average fuel consumption is above the value of the median inlier vehicles for the same model and on the same route type.

Finally, the schema shown in Figure 2 includes several evaluation steps. First, a "Model Evaluation", where the performance of the model is measures just like any other ML regression algorithm. We analyse the performance with the following metrics: R2 and the Mean Average Precision Error (MAPE).

Along with this, we propose novel evaluation steps that evaluates the explanations against prior domain knowledge. The quantitative evaluation of XAI explanations in order to see if they are aligned with prior domain knowledge is what some authors have identified as the property of being "consistent with a priori beliefs" [29, 30].

Following this, first, we use the individual explanations generated by the aforementioned solution, and after applying BR1, BR2 and BR3, we aggregate the relative impact in the average fuel consumption following the categories described in Table 2 from [5] in order to see if the impact per category is aligned with the SOTA (Evaluation 2 in Figure 2). Second, we compare the new average fuel consumption (after applying the recommendations from the Daily Explanations step) to the catalog fuel reference for vehicles of the same make, model, year, fuel type and on that specific route type (city, combined or highway). The intuition behind this is that if we remove the extra fuel due to driving behaviour, traffic conditions... the vehicle's fuel should be close to its catalog reference. The databases that we use to get this catalog fuel reference are [31], [32], [33] and [34]. A consideration to take into account is that there may be many entries in the databases for a same make, model, year, fuel type and route type. In this cases, we use as catalog reference the median fuel value over all those entries.

## 4 | EVALUATION

We use the XAI proposal of [28] over different industry datasets to evaluate the hypotheses described below. For all these hypotheses we use as source of information the feature-relevance explanations yielded by the XAI algorithm, since they account for the individual impact from the different features in the fuel consumption. The hypotheses are connected to the evaluation steps mentioned before in Figure 2.

Regarding the "Model Evaluation" step:

- **Hypothesis 1 (H1):** The model's performance from the XAI algorithm in terms of the median Mean Average Precision Error (MAPE) and Adjusted R2 is good enough according to the references from the literature on each dataset.

For the "Domain Knowledge Evaluation" (Evaluation 1) step:

- **Hypothesis 2 (H2):** The relative fuel impact explained for the different feature subclasses from Tables 10 and 11 is between the literature limits shown in [5], or at least below the maximum limit.

As for the "Domain Knowledge Evaluation" (Evaluation 2) step:

- **Hypothesis 3 (H3):** The relative fuel impact explained for the vehicle-dates with anomalous fuel consumption is not significantly lower than the relative extra fuel detected by the outlier detection algorithm.
- **Hypothesis 4 (H4):** The new average fuel consumption after applying the recommendations from the "Daily Explanations" step is similar to both the catalog reference for that same vehicle's make, model, year, fuel type and on that route type. It will aso be similar compared to the median historical value of the vehicle's from the same group without fuel anomalies. This will be measured in terms of the MAPE against those reference values.

The reference values for MAPE in H1 and H5 are the ones that appear in [35]. Those reference values are originally expressed for forecasting models, but we will use them for this use-case of regression, since MAPE is a metric also used for regression models [36].

- < 10: Highly accurate forecasting
- 10 − 20: Good forecasting
- 20 − 50: Reasonable forecasting
- > 50: Inaccurate forecasting

Adjusted R2 indicates the proportion of the variance in the target feature that can be predicted using the input features. Even though this metric significantly depends on the context and units of the target feature [37, 38], making if difficult to find general threshold values that indicate if it is good or not, there are some guidelines that may be considered. One of these guidelines is the proposal of [39], that mentions the following thresholds:

- 0.67: Substantial
- 0.33: Moderate
- 0.19: Weak

## 4.1 | Datasets

The data source is the real-time feed of data retrieved by a telematics device connected to the to the on-board diagnostics (OBD) port. Particularly, we retrieve the data from devices connected to OBD-II port, since they allow an easy and direct retrieval of relevant features, such as the fuel consumption through the Engine Fuel Rate with the

Parameter ID (PID) 015E [8]. A sample of these raw data with a csv structure can be seen in (Table 4), and is also available at [40].

| time_tx | vehicle_id | variable_id | variable_value |
|---|---|---|---|
| 2020-10-31 00:02:34.073000+00:00 | b123 | EngineSpeed | 1200 |
| 2020-10-31 00:12:34.073000+00:00 | b124 | VehicleSpeed | 55 |
| 2020-10-31 01:12:34.073000+00:00 | b125 | EngineSpeed | 1200 |
| 2020-10-31 02:02:34.073000+00:00 | b124 | TripFuel | 3.1 |

**TABLE 4** Sample of the received data from the IoT devices

This data feed is then aggregated with a daily frequency into daily aggregations, building what we call the *Fleet Analytics Record* (FAR), a database for each fleet owner where there is a record for every vehicle and date with different features related to the fuel consumption, as indicated in Tables 10 and 11. It also includes other features related to the vehicle itself, such as the Vehicle Identification Number (VIN), make, model, manufacturing year or the fuel type. Over the FAR, we apply several quality assurance analysis, where we discard records that are not meaningful or that may not be useful for training the model. The criteria followed is:

- Remove records with missing trip distance, or with a low trip distance in that day (Km < 5).
- Remove records with missing fuel, or with a too small fuel consumption, according to Equation 2. This Equation is used first for discarding vehicles with an average fuel consumption that is too low (below the lower limit). Then, after the Noise Elimination step, it will be applied again with the remaining data for obtaining the upper limit for the univariate anomaly detection step from Figure 2.
- Remove records with a potential wrong fuel value due to being extremely high. Besides having fuel anomalies that correspond to certain feature values, there is also noisy data regarding fuel consumption that needs to be eliminated in order to help the training of the ML model. We also use Equation 2. This data points are also removed before computing the final limits for the anomalous fuel consumptions that are not noisy data at the univariate anomaly detection step from Figure 2.

Finally, we fill the other missing values with the median historical value from the fleet using vehicles from the same make, model, year and fuel type to fill the missing feature value of a particular vehicle on a particular date.
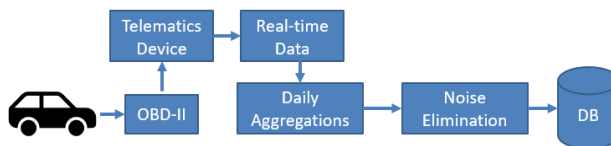


**FIGURE 5** Data feed process for obtaining the databases.

This process is done for different fleets independently, resulting in an individual data set for each one of them. With that, we use 9 data sets from different fleets, as indicated in Table 5. These data sets contain different types of vehicles that are identified with two groups of variables. The first one is the vehicle's make, model, year and fuel type. Since fuel consumption depends on the type of vehicle (among other things), we use the Vehicle's Identification

Number (VIN) to identify those variables. With that, we get the different types of models that appear in column "N models". Along with that, since some models may have similar fuel consumption, we add an additional variable, named vehicle class, that groups together those vehicles (e.g. "Large Pick-Ups"). This vehicle class is inferred directly from the historical mean average fuel consumption, following the classification Table 6 that appears in [41, p. 18]. With that, we are conducting the analyses over fleets of vehicles that are different among themselves, in order to provide results that are as general as possible. Those fleets include passenger fleets (such as D1) of vehicles, as well as heavy-duty vehicles like trucks (such as D3). We are also covering different fleet sizes, such as "Large/Enterprise" (D1 and D2), "Medium" (D3, D4, D5 and D6), and "Small" (D7, D8 and D9), following the categorization of [42], where fleets with more than 500 vehicles are considered "Large/Enterprise"), fleets between 50 and 499 "Medium", and fleets with less than 49 vehicles "Small". This is indicated in column "Size". Finally, column "N outliers" indicate the vehicle-dates with fuel anomalies, according to the univariate outlier detection from Section 3.

| Fleet | N vehicles | N models | N points | N outliers | Size | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Class 6 | Class 7 | Class 8 | Class 9 | Class 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D1 | 1551 | 16 | 218038 | 5770 | Large | 1479 | 34 | 1 | 37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| D2 | 1564 | 16 | 120605 | 1809 | Large | 201 | 697 | 75 | 588 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| D3 | 316 | 44 | 65285 | 10475 | Medium | 243 | 5 | 1 | 9 | 10 | 5 | 13 | 9 | 21 | 0 | 0 |
| D4 | 252 | 14 | 35283 | 1915 | Medium | 4 | 178 | 61 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| D5 | 165 | 20 | 22402 | 724 | Medium | 165 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| D6 | 143 | 20 | 18555 | 2002 | Medium | 1 | 28 | 100 | 5 | 3 | 0 | 0 | 0 | 5 | 1 | 0 |
| D7 | 33 | 5 | 8450 | 942 | Small | 0 | 0 | 0 | 2 | 3 | 0 | 0 | 0 | 10 | 18 | 0 |
| D8 | 20 | 5 | 2125 | 349 | Small | 5 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| D9 | 3 | 2 | 269 | 10 | Small | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 |

**TABLE 5**  Dataset description, including the number of datapoints, number and type of vehicles.

| Class | Applications | Gross Weight Range (lb) | L100Km_min | L100Km_max | L100Km_med | Vehicle Class |
|---|---|---|---|---|---|---|
| 1c | Cars only | (3200)-6000 | 7.12 | 9.41 | 8.27 | 0 |
| 1t | Minivans, Small SUVs, Small Pick-Ups | (4000)-6000 | 9.40 | 11.76 | 10.58 | 1 |
| 2a | Large SUVs, Standard Pick-Ups | 6001-8500 | 11.20 | 11.76 | 11.48 | 2 |
| 2b | Large Pick-Up, Utility Van, Multi-Purpose, Mini-Bus, Step Van | 8501-10,000 | 15.68 | 23.52 | 19.60 | 3 |
| 3 | Utility Van, Multi-Purpose, Mini-Bus, Step Van | 10,001-14,000 | 18.09 | 29.40 | 23.74 | 4 |
| 4 | City Delivery, Parcel Delivery, Large Walk-in, Bucket, Landscaping | 14,001-16,000 | 19.60 | 33.60 | 26.60 | 5 |
| 5 | City Delivery, Parcel Delivery, Large Walk-in, Bucket | 16,001-19,500 | 19.60 | 39.20 | 29.40 | 6 |
| 6 | City Delivery, School Bus, Large Walk-in, Bucket | 19,501-26,000 | 19.60 | 47.04 | 33.32 | 7 |
| 7 | City Bus, Furniture, Refrigerated, Refuse, Fuel Tanker, Dump,Tow, Concrete,Fire Engine,Tractor-Trailer | 26,001-33,000 | 29.40 | 58.80 | 44.10 | 8 |
| 8b | Tractor-Trailer: Van, Refrigerated, Bulk Tanker, Flat Bed (combination trucks) | 33,001-80,000 | 31.36 | 58.80 | 45.08 | 9 |
| 8a | Dump, Refuse, Concrete, Furniture, City Bus, Tow, Fire Engine (straight trucks) | 33,001-80,000 | 39.20 | 94.09 | 66.64 | 10 |

**TABLE 6**  Vehicle classes according to their average fuel consumption, as appears in [41, p. 18]

As already mentioned, the features considered for each of those data sets appear in Tables 10 and 11. Column "Name" includes a descriptive name for each of the features, and column "Description" contains a descriptive text about each of them. "Unit" indicates the metric units associated to each of the features, and "Notes" contains a description about some of the variables and why they may impact in fuel consumption (particularly for the ones that are not trivial). The column "Type" shows the type of impact that those features have in fuel consumption. If the type is "Positive" it indicates that increasing that feature value will normally *increase* fuel usage. An example of this is the number of events with high RPM; more events lead to more fuel consumption. On the contrary, if the type is "Negative", it indicates that increasing that feature value will normally *decrease* fuel usage. An example of this is the time using speed control; more time using it should lower the fuel consumption (versus not using it). Another

example is the tire pressure; when they decrease, the fuel used will increase. Column "Reference Zero" indicates the columns that in order to see the impact in the fuel consumption are set to zero. For instance, for obtaining the feature impact for a variable like "rpm_high", this variable is set to 0 for calculating the reduction in the fuel consumption due to it by seeing the decrease with respect to the current feature value. For the remaining features the reference is, by default, the median value for that feature over the vehicles with fuel inliers from the same vehicle model. Finally, columns "Category" and "Subcategory" refer directly to the same columns from Table 2 from [5]. The columns that do not have a value in both of these columns are columns that are not features used for explaining the fuel (they are relevant for the data set, and some of them are even used in the model, like the vehicle model, but they are not used for explanations). Among these columns is the main driving context detected for each day ("route_type"). This is calculated as follows:

- IF $per\_time\_city \leq low\_th\_time$ AND $trip\_kms \geq th\_kms$ THEN $route\_type = hwy$
- ELSE IF $per\_time\_city \geq high\_th\_time$ AND $trip\_kms \leq th\_kms$ THEN $route\_type = city$
- ELSE $route\_type = combined$

With $th\_kms = 30$, $low\_th\_time = 0.5$ and $high\_th\_time = 0.65$. Thus, we categorize each vehicle-date with a particular route type that may be "city", "highway" or "combined", depending on the total trip kms (trip_kms) and the value of the variable per_time_city. An example of this route type categorization, using the threshold values aforementioned, appears in Figure 6.
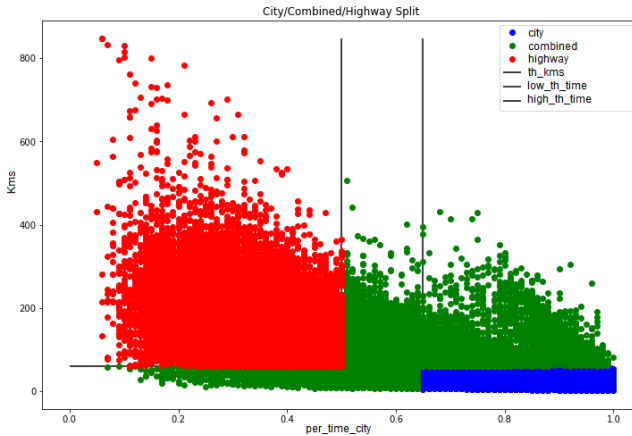


**FIGURE 6** Daily categorization of route types based on the trip distance (Km) and per_time_city for the data set D1.

The categories considered are "Auxilary Systems" (for all the features that imply an additional electrical energy consumption), "Driving Behaviour" (driver-related features), "Road Conditions", "Vehicle Conditions" and "Weather Conditions". Regarding "Vehicle Conditions", we have included additional variables within the "Other" subcategory with respect to [5] (e.g. the additional fuel consumption when the DEF level is low), so it does not match the ones covered in that review. Because of that, this subcategory will not be used for checking the hypotheses already mentioned. For "Rain" subcategory, since the review only provides one reference value, we will only check H1 (since there

are no limits per se).

Finally, the dependent variable is the average fuel consumption, calculated as follows:

$$avg\_fuel\_consumption = \frac{trip\_fuel\_used}{trip\_kms} \times 100 \tag{4}$$

## 4.2 | Results

Considering a train/test split for each data set of 90/10, we get the results shown in Table 7. As we can see, D1, D2, D4, D5, D6, D7 and D8 are within the "highly accurate forecasting" category, while D3 and D9 are within the "good forecasting" one. Thus, the model is able to infer sufficiently good relationships between the input data and the fuel consumption, and H1 is validated. Because of that, it can be used for extracting explanations in order to evaluate the remaining hypotheses. In fact, the explanations for all those fleets over that 4 months period yielded explanations for 78392 vehicle-dates. When considering vehicles with a median MAPE value over the test set if "Good forecasting" or better, the explanations covered corresponds 96.7%, and 76.2% when considering vehicles with a "Highly accurate forecasting". Complementing this, in Table 7 we see the adjusted R2 value on the test set for each data set. Every data set is within the "substantial" R2 category.

| Fleet | MAPE | Adjusted R2 |
|-------|------|-------------|
| D1 | 8.0 | 0.80 |
| D2 | 8.0 | 0.84 |
| D3 | 11.0 | 0.96 |
| D4 | 10.0 | 0.64 |
| D5 | 8.0 | 0.72 |
| D6 | 7.0 | 0.90 |
| D7 | 7.0 | 0.83 |
| D8 | 8.0 | 0.69 |
| D9 | 15.0 | 0.84 |

**TABLE 7** MAPE median results and adjusted R2 for each fleet.

### 4.2.1 | Evaluation of Explanations

For evaluating the explanations, we focus on the 4 months of data where the winter period is included (in order to be able to assess the impact of the ambient temperature). Using the models, we get the explanations for each vehicle-date for that period of data, and we aggregate the median feature impact values per subcategory and per vehicle fleet. The median results regardless of the fleet appear in Figure 8, and the median results considering fleet and including the limits from the SOTA appear in Figure 7. For the analyses, we have considered only the vehicles that have a median MAPE over the test set of "Good forecasting" or better (unless otherwise indicated).

In Figure 8 we see how the absolute relative impact for each subcategory is below the limits show in Table 2. This is shown clearer in Figure 7, where we see that for all the data sets and for all the feature subcategories the relative
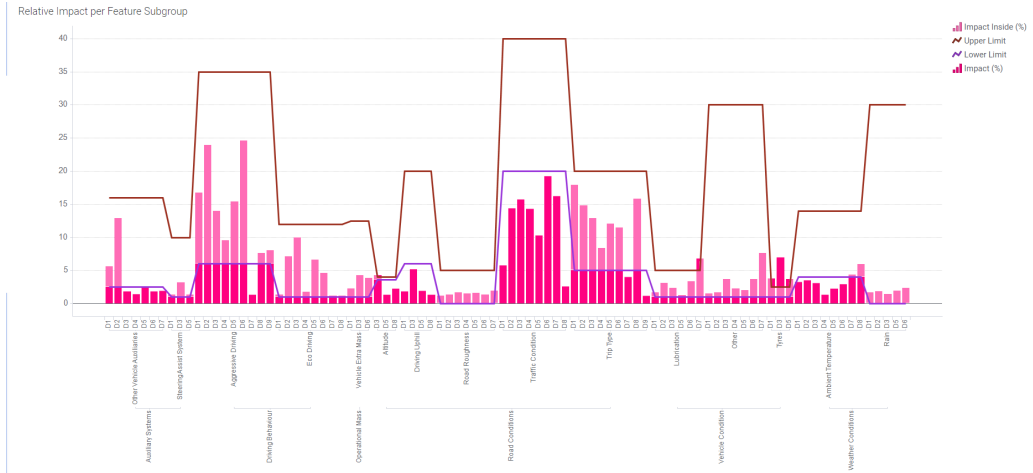
**FIGURE 7** Median feature impact per Category-Subcategory-Fleet and the corresponding limits from the literature [5]

impact is below the reference values.

Complementing this, in Table 2 we see what combinations of subcategories-datasets are within the limits from the literature. For 46 combinations, out of the 78 (without the Subcategories of "Other" and "Rain", as mentioned before), the feature relevance is within the limits from the SOTA. The remaining 32 that are not within the limits is because they are either lower than the minimum value used, or higher (for all the three data sets where tyres are relevant, and Lubrication for D7). "Aggressive Driving", "Eco-Driving", "Trip Type" and "Road Roughness" are the Subcategories that are both common in all data sets while having an aggregated feature impact that is within the literature limits. Others, such as "Steering Assist Systems" and "Vehicle Extra Mass" are also fully within the limits, but they are features that are relevant only for some data sets.

With Figure 8 we see the individual impact per vehicle and date, for all the data sets considered together. As the Figure shows, "Other Vehicle Auxiliaries", "Steering Assist Systems", "Aggressive Driving", "Eco Driving", "Vehicle Extra Mass", "Road Roughness", "Trip Type, and "Lubrication" have a median value per vehicle-date that is within the limits from the SOTA. For some Subcategories, such as "Steering Assist Systems", "Vehicle Extra Mass", and "Road Roughness", the upper whisker value from the boxplot is also within the SOTA limits. Other subgroups where the median value was not within the limit (because it was below the lower limit), the upper whisker is within the SOTA limits. This is the case of "Ambient Temperature", "Traffic Condition" and "Driving Uphill". Also, we see, however, that even though the impact per Subcategory normally does not exceed the upper values reported, there are data points where the impact is above the thresholds from the literature.

With that, H2 is validated for the 74 out of the 78 combinations of subcategories-data sets since they have an influence in the fuel consumption because the relative impact is always below the maximum SOTA values, and in some cases, its even between them. The exceptions are all the cases of the impact due to features associated to the "Tyres" subcategories, and "Lubrication" for D7.

For H3, we analyse the extra fuel explained through XAI with respect to the extra fuel indicated by the limits generated by the outlier detection method from the previous Section. The intuition behind it is that even though the XAI whitebox algorithm is not trained over all the potential causes that may impact in the fuel consumption, it is
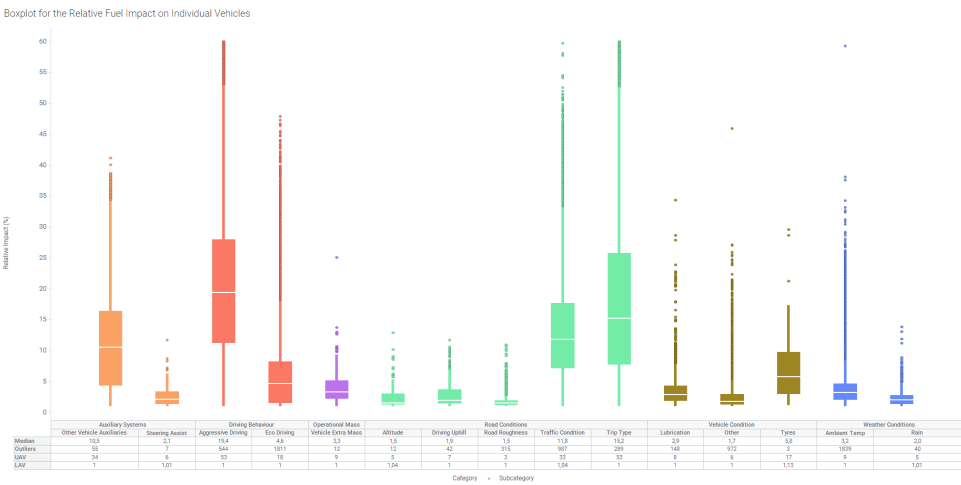
Boxplot for the Relative Fuel Impact on Individual Vehicles

| | Auxiliary Systems | | Driving Behaviour | | Operational Mass | Altitude | Driving Uphill | Road Conditions | Traffic Condition | Trip Type | Lubrication | Vehicle Condition | | Tyres | Weather Conditions | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Other Vehicle Auxiliaries | Steering Assist | Aggressive Driving | Eco Driving | Vehicle Extra Mass | | | Road Roughness | | | | Other | | | Ambient Temp | Rain |
| Median | 10,5 | 2,1 | 19,4 | 4,6 | 3,3 | 1,5 | 1,9 | 1,9 | 11,8 | 15,2 | 2,9 | 1,7 | 5,8 | 3,2 | 2,0 |
| Outliers | 55 | 7 | 544 | 1811 | 12 | 12 | 42 | 315 | 987 | 289 | 148 | 972 | 3 | 1839 | 40 |
| UAV | 34 | 6 | 53 | 18 | 9 | 5 | 7 | 5 | 33 | 53 | 8 | 6 | 17 | 9 | 5 |
| LAV | 1 | 1,01 | 1 | 1 | 1 | 1,04 | 1 | 1 | 1,04 | 1 | 1 | 1 | 1,13 | 1 | 1,01 |

Category = Subcategory

**FIGURE 8** Subcategory fuel impact per vehicle-date.

| Fleet | Median (explained) | Median (outliers) | p-value |
|---|---|---|---|
| D1 | 0.31 | 0.09 | <0.01 |
| D2 | 0.45 | 0.08 | <0.01 |
| D3 | 0.29 | 0.09 | <0.01 |
| D4 | 0.20 | 0.14 | 0.21 |
| D5 | 0.32 | 0.07 | 0.02 |
| D6 | 0.45 | 0.08 | <0.01 |
| D7 | 0.30 | 0.23 | 0.83 |
| D8 | 0.12 | 0.06 | 0.08 |
| D9 | 0.09 | 0.03 | 0.32 |

**TABLE 8** Relative impact of extra fuel explained versus extra fuel with respect of the outlier limit.

enough to explain at least that extra anomalous fuel. In Figure 9 we see that the comparison between the relative extra fuel explained by the XAI method versus the extra fuel shown by the outlier detection algorithm for each of the models within every fleet data set. We see that, in fact, for the majority of the cases the extra fuel explained is actually superior than the extra anomalous fuel detected. Table 8 shows that comparison for each data set and for every vehicle and date. It shows that D4, D5, D7, D8 and D9 are the only data sets where there are no significant differences between anomalous fuel and explained extra fuel. In all the remaining cases, the explained fuel is actually superior to the outlier part. So, the XAI method is actually able to explain at least the anomalous part of the fuel in all the cases, validating H3.

In order to check H4, we get the MAPE metric from the new average fuel consumption for each vehicle-date after applying the recommendations, and compare it to the catalog fuel consumption for the same make, model, year, fuel type and route type, as mentioned in Subsection 3.3. The same procedure is applied for comparing it against the median fuel consumption from the vehicles-dates data points corresponding to the same group, and on the same
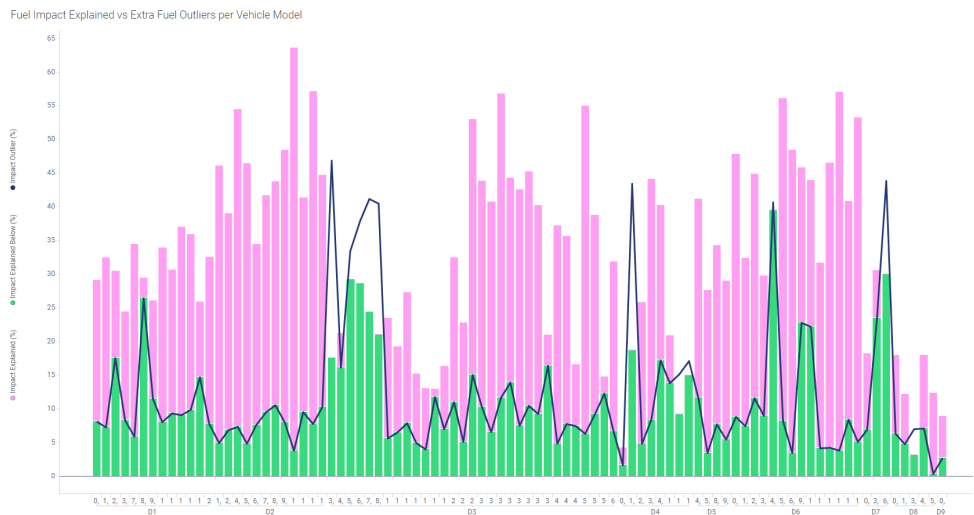
**FIGURE 9**   Relative extra fuel explained versus the relative extra fuel by the outlier detection method for each of the vehicle models within every dataset.

route type, that are not identified as an anomalous fuel consumption. Results appear in Table 9. MAPE 1 corresponds to the median MAPE versus the catalog fuel, MAPE 2 corresponds to the median MAPE versus the median fuel inlier vehicles, and MAPE 3 is the same as MAPE 2 but considering only explanations for outlier vehicles. Considering MAPE 1, we see that for every data set, except for D2 and D9, the new average fuel consumptions after applying the recommendations are similar to the catalog fuel ("Reasonable forecasting" or better). D6 does not have any results in the catalog comparisons because the make, models and fuel types did not appear within the databases used in Subsection 3.3. Columns "% MAPE 1 < 0.5", "% MAPE 1 < 0.2" and "% MAPE 1 < 0.1" show the percentage of vehicle-date explanations that have an individual MAPE of 0.5, 0.2 or 0.1 respectively.

Regarding the comparison against the median inliers, the results are better. All the data sets yield a median MAPE from the "Reasonable forecasting" category or better. There are significant differences in the case of D9, meaning that the fuel consumption of the inliers is different from the catalog (in the case of D9, the data set is small, so the anomaly detection process may not yield accurate results). For the rest of the cases, even though is smaller, is similar.

The results either improve or are similar when considering only the fuel outliers in the explanation process. In this case, the worst result is D7, with a MAPE of 0.4. The rest of the data sets are either in the "Good forecasting" category or close to it. In some cases, like D2, the results are improved by reducing the MAPE by 0.2.

Finally, the column "% below catalog" show the percentage of vehicle-dates that are receiving a recommendation that turns the average fuel consumption (L/100Km) below the catalog reference (with an offset of 1 L/100Km). This metric should be minimized, because the target fuel should not be below the catalog reference (is a value that is not physically reachable). This indicates data points that the model is nor explaining properly (its overestimating the potential fuel reduction). The best cases are D1, D7 and D9 where this metric is 3.2%, 3.6% and 0% respectively.

The previous analysis can be enhanced by checking the fuel reduction considering each vehicle model and route type with respect to the catalog reference. In the case of D1, we explicitly had the vehicle's makes (so it was not needed to retrieve them from the VIN decoding process). Because of that, we obtained there exactly catalog fuel consumption from [43] and [44]. The results appear in Figure 10. There, we only see 4 cases where the new average

| Fleet | MAPE 1 | MAPE 2 | MAPE 3 | % MAPE 1 <0.5 | % MAPE 1 <0.2 | % MAPE 1 <0.1 | % MAPE 2 <0.5 | % MAPE 2 <0.2 | % MAPE 2 <0.1 | % below catalog |
|-------|--------|--------|--------|------------|------------|------------|------------|------------|------------|---------|
| D1 | 0.17 | 0.11 | 0.17 | 92.6 | 56.8 | 30.5 | 99.2 | 73.4 | 45.2 | 3.2 |
| D2 | 0.5 | 0.41 | 0.21 | 22.1 | 6.3 | 3.1 | 67.7 | 17.9 | 8.6 | 34.9 |
| D3 | 0.5 | 0.28 | 0.25 | 34.9 | 6.4 | 3.0 | 83.5 | 35.0 | 17.9 | 42.0 |
| D4 | 0.22 | 0.18 | 0.14 | 83.7 | 46.3 | 23.9 | 97.6 | 57.0 | 24.6 | 6.3 |
| D5 | 0.39 | 0.29 | 0.19 | 27.3 | 7.0 | 3.0 | 92.6 | 28.3 | 12.9 | 31.3 |
| D6 | | 0.37 | 0.22 | | | | 72.4 | 19.7 | 8.0 | |
| D7 | 0.23 | 0.07 | 0.4 | 13.5 | 7.8 | 4.1 | 91.4 | 81.3 | 62.9 | 3.6 |
| D8 | 0.12 | 0.05 | 0.1 | 36.8 | 24.9 | 15.5 | 100.0 | 93.5 | 75.5 | 10.8 |
| D9 | 1.12 | 0.07 | 0.22 | 0.0 | 0.0 | 0.0 | 100.0 | 90.9 | 61.4 | 0.0 |

**TABLE 9** Different MAPE metrics on each of the datasets versus the catalog fuel consumption (MAPE 1), the median inliers (MAPE 2), or considering only the vehicles with outlier fuel consumption versus the inliers (MAPE 3).

fuel is below the catalog reference.
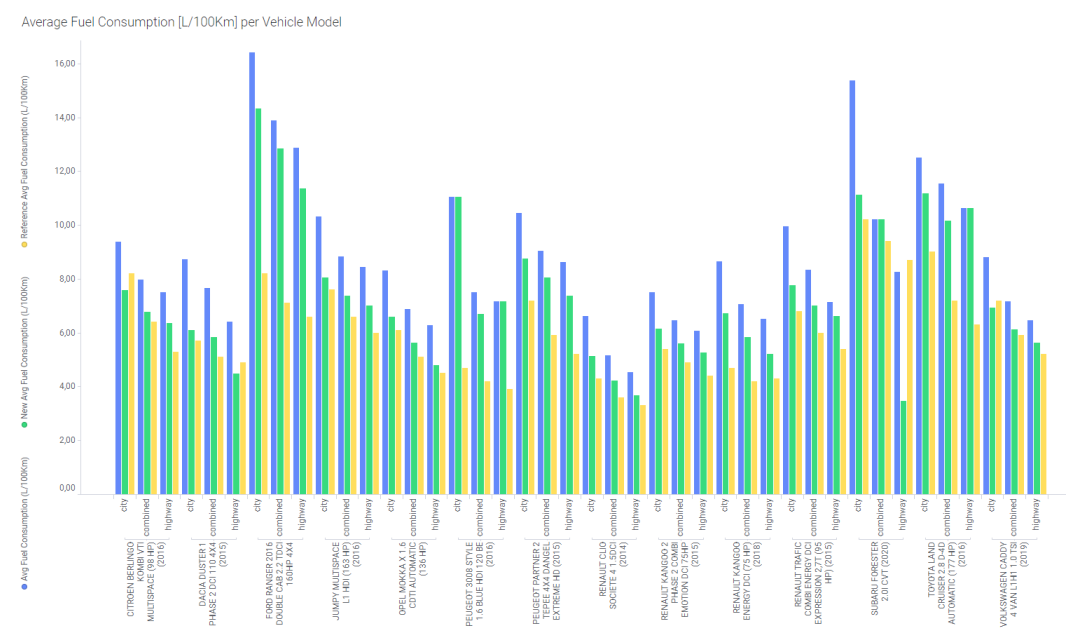


**FIGURE 10** Average fuel consumption (L/100Km) for the vehicle's models from data set D1 in each route type (city, combined, highway), before and after applying the recommendations, and compared to the catalog reference. .

### 4.2.2 | Potential Impact

The previous information showed what variables are impacting on the fuel consumption of individual vehicles, and how much fuel could be reduced by acting upon them through the explanations provided. This information is useful for having a full view over the whole fleet and seeing the extra fuel consumption that it is taking place because of those factors. Even more, we can focus on specially actionable factors, such as driving behaviour, in order to see the impact on the fuel consumption due to the driving style. Figure 11 shows the fuel consumption on each of the fleets over the four months considered, together with the extra fuel consumption from driving behaviour, and the extra fuel consumption due to the remaining factors.
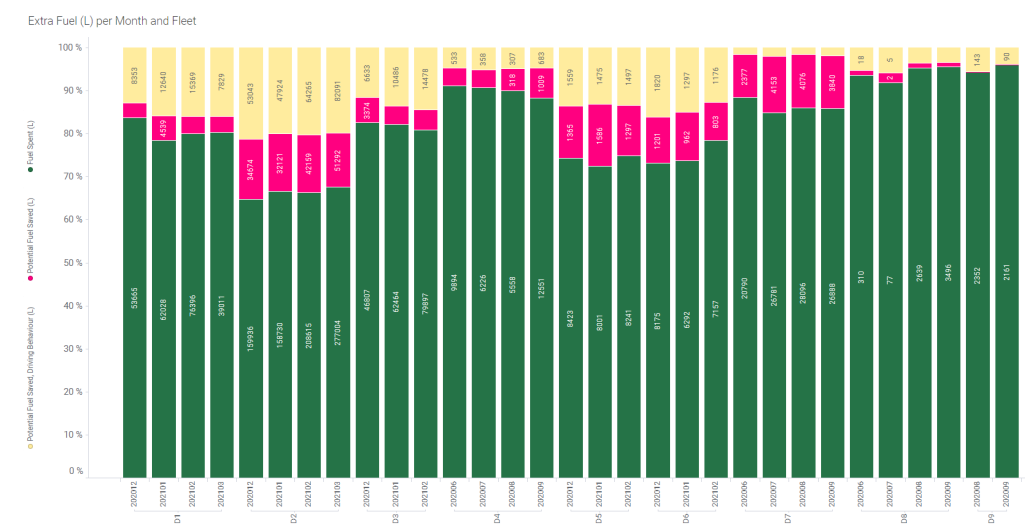


**FIGURE 11**   Monthly fuel consumption (L) for each fleet over the different months, along with the part of that fuel that corresponds to the extra fuel due to driving behaviour, together with the extra fuel from the remaining factors.

Focusing on D1 (since it is the fleet with more information and that provided better results), we see that the relative impact of all the features is between 16% and 22%, and for driving behaviour only, it is between 13% and 16%. Taking as an example the month of February, we see that there are 15546 extra litres spent due to driving behaviour. Reducing it would have a positive impact both in the expenses from the fleet, as well as in the environment. Since the vehicles from D1 are mostly diesel, using the conversion to $CO_2$ from [3], where 2.67633 Kg of $CO_2$ are emitted per liter of diesel spent, the extra $CO_2$ emissions in one month due to driving behaviour is between 22330 and 41085 Kg.

### 4.3 | Software Used

The main libraries used for the work done in this paper are the following:

- EBM [45]. We used the default parameters from the library for all the analyses.

- Hypothesis contrasts [46]

## 4.4 | Limitations

First of all, our proposal studies the influence on fuel usage for petrol and diesel vehicles altogether. The independent analysis for petrol and diesel vehicles may yield different results. Also, we do not cover hybrid vehicles within our study. Though we focused on actionable features for analysing the impact on the fuel consumption through XAI, there are other features that could be elicited. Regarding the EBM algorithm, we only used the individual feature relevance of each variable for building the recommendations, not considering possible pairwise terms if they exist. Finally, as we saw for the case of harsh turns in Figure 4, the relationships between an input feature and output are not monotonic. It would be interesting to analyse how the results differ when applying monotonic constraints.

## 4.5 | Future Work

We see several possible lines of work following this paper. First of all, the set of variables used could be enhanced. Even though we use up to 70 features per dataset, not all the subcategories mentioned within the SOTA are covered. For instance, we do not use any feature that measures the usage of a trailer towing or roof racks. Also, the analyses could be complemented with the usage of other XAI feature relevance techniques for generalizing the results obtained. Finally, even though the domain knowledge is considered before the model training and explanation generation when eliciting the features, for the remaining steps (business rules for filtering the explanations, metric analysis...) is something that is being applied post hoc. Applying all the knowledge before training the model could potentially yield better results.

## 5 | CONCLUSION

In this paper we followed the literature regarding the factors that impact in the fuel consumption of a vehicle, and we used XAI in order to see if it is possible to explain and quantify that impact with these techniques. For that, we used a variation over the Explainable Boosting Machines (EBM) algorithm, a type of whitebox algorithm that yields explanations in terms of feature relevance. We trained the model with a set of up to 70 features in order to predict the fuel consumption of diesel and petrol vehicles, using several real-world industry datasets for very different types of fleets (passenger cars, trucks...). Then, we generated explanations combining the information provided by the EBM algorithm and the feature taxonomies from the SOTA regarding the factors that affect fuel consumption.

We saw how XAI can be used for understanding the factors that impact in the fuel consumption of a vehicle in a quantitative way. First, we saw that EBM whitebox algorithm, which provides feature relevance explanations, yields good performance metrics for modelling the relationship between input factors and fuel consumption. Then, we saw that the explanations are coherent with the previous analyses from the SOTA regarding the impact that those features should have in the fuel consumption of a vehicle. We also saw that for vehicles that have an anomalous fuel consumption, according to an unsupervised anomaly detection algorithm, EBM is generally able to explain even more extra fuel consumption than the one identified by the outlier detection algorithm. Then, we evaluated the potential fuel saving from our proposal with respect to external databases that provide the catalog fuel consumption for the vehicle models that we have used in our work. We saw that reducing the fuel consumption following the explanations from EBM reduced the fuel consumption to values very close to catalog fuel references. Finally, we assessed the

potential impact that our proposal may have in a particular fleet of vehicles in terms of both the extra fuel that may be saved by acting upon the actionable factors, as well as the associated reduction in CO2 emissions.

## 5.1 | CRediT authorship contribution statement

**Alberto Barbado**: Conceptualization, Investigation, Writing - original draft, Writing - review and editing, Visualization, Formal Analysis, Methodology. **Óscar Corcho**: Writing - review and editing, Supervision.

## 5.2 | Acknowledgements

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# 6 | ANNEX

| Variable | Description | Units | Type | Reference Zero | Category | Subcategory |
|---|---|---|---|---|---|---|
| vehicle id | Vehicle's unique ID number | | | | | |
| date | Date (DD/MM/YYYY) | | | | | |
| vehicle model | Vehicle's model ID (associated to its make/model/year) | | | | | |
| make | Vehicle's make | | | | | |
| model | Vehicle's model | | | | | |
| year | Vehicle's manufacturing year | | | | | |
| VIN | Vehicle identification number | | | | | |
| route type | Route type associated to that date (highway, city, combined) | | | | | |
| vehicle class | Vehicle class associated to this vehicle (depends on its average fuel consumption; e.g. Large SUVs) | | | | | |
| diesel_detected | Indicates if the vehicle is diesel or not (detected) | | | | Fuel Characteristics | |
| duration air conditioner on | Hours with air conditioner on | hours | Positive | Yes | Auxiliary Systems | Air Conditioning |
| duration ABS on | Time driving with traction system (ABS) activated. Additional energy supply required; Imply road gripping problems | hours | Positive | Yes | Auxiliary Systems | Steering Assist Systems |
| duration lights left on | Time with lights left on | minutes | Positive | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| duration with hazard lights on | Time driving with hazard lights on. More time driving with hazard lights on may inderectly imply more fuel consumption (because there are road impediments, problems with the car...) | hours | Positive | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| duration with change filter light on | Time driving with fuel filter change light on. May indirectly imply more fuel consumption | hours | Positive | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| number of cranking events below 10V | Number of cranking events below 10 V. Cranking voltage should not fall below 10V (and its optimal value is 6x2.1); otherwise, it may indicate a problem with the battery (p.e. a cell is dead) | None | Negative | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| duration with diesel particulate filter on | Time driving with diesel particulate filter on | hours | Positive | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| duration PTO | Hours using power take-off | hours | Positive | Yes | Auxiliary Systems | Other Vehicle Auxiliaries |
| count harsh brakes | Total harsh brake events. | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| count harsh turns | Total harsh turn events. | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| count jackrabbit | Total jackrabbit events | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| mean braking acc | Mean value for braking acceleration | m/s2 | Positive | | Driving Behaviour | Aggressive Driving |
| mean forward acc | Mean value for front acceleration | m/s2 | Positive | | Driving Behaviour | Aggressive Driving |
| mean up down acc | Mean value for up/down acceleration | m/s2 | Positive | | Driving Behaviour | Aggressive Driving |
| mean side to side acc | Mean value (absolute) for side to side acceleration | m/s2 | Positive | | Driving Behaviour | Aggressive Driving |
| mean speed city | Mean value of the speed within city. Speed events are considered "city" if speed<50 km/h | Km/h | Positive | | Driving Behaviour | Aggressive Driving |
| mean speed hwy | Mean value of the speed within highways. Speed events are considered "highway" if speed>=50 km/h | Km/h | Positive | | Driving Behaviour | Aggressive Driving |
| rpm high | Events with engine's speed (RPM) equal or above 1900 | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| rpm red | Events with engine's speed (RPM) above 3500 and vehicle speed below 40 Km/h | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| rpm orange | Events with engine's speed (RPM) above 3500 and vehicle speed between 40 and 80 Km/h (included) | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| rpm yellow | Events with engine's speed (RPM) above 3500 and vehicle speed above 80 Km/h | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| count speed over 120 | Number of events above 120 Km/h | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| count speed over 90 | Number of events above 90 Km/h | none | Positive | Yes | Driving Behaviour | Aggressive Driving |
| duration ecomode on | Hours with eco-mode on | hours | Negative | | Driving Behaviour | Eco Driving |
| ignition events | Events of engine's ignition | none | Positive | | Driving Behaviour | Eco Driving |
| duration speed control | Hours driving with speed control set on | hours | Negative | | Driving Behaviour | Eco Driving |
| count neutral | Total events of gear position in neutral | none | Positive | | Driving Behaviour | Eco Driving |
| count reverse | Total events of gear position in reverse | none | Positive | | Driving Behaviour | Eco Driving |

**TABLE 10** General variables and features used for predicting the fuel usage, with their associated categories and subcategories, according to [5] for Auxiliary Systems and Driving Behaviour .

| Variable | Description | Units | Type | Reference Zero | Category | Subcategory |
|---|---|---|---|---|---|---|
| duration extra passenger | Time with extra passenger | hours | Positive | | Operational Mass | Vehicle Extra Mass |
| height | Mean height where the vehicle was driving. | meters | Negative | | Road Conditions | Altitude |
| duration uphill | Time while driving uphill. | hours | Positive | | Road Conditions | Driving Uphill |
| duration road with bumps | Time while driving in a road with bumps | hours | Positive | | Road Conditions | Road Roughness |
| duration idle | Total time with idle drive | hours | Positive | | Road Conditions | Traffic Condition |
| trip kms | Distance driven | Kms | Negative | | Road Conditions | Trip Type |
| per time city | Percentage of time spent driving within city | % | Positive | | Road Conditions | Trip Type |
| duration with hazard lights on | Time driving with hazard lights on. Inderectly imply more fuel consumption (because there are road impediments, problems with the car...) | hours | Positive | | Road Conditions | Trip Type |
| duration oil low light on | Time driving with low oil light on. Low oil increases friction, increases heating | hours | Positive | Yes | Vehicle Condition | Lubrication |
| duration oil change light on | Time driving with oil change light on. When oil change needed: increased friction, increased heating | hours | Positive | Yes | Vehicle Condition | Lubrication |
| duration oil change due light on | Time driving with oil change due light on | hours | Positive | Yes | Vehicle Condition | Lubrication |
| mean engine oil temp | Mean temperature reached by the engine's oil | ºC | Positive | | Vehicle Condition | Lubrication |
| mean transmission oil temp | Mean temperature for the transmission oil. If temperature is not high enough, worse lubrication, worse milage | ºC | Postive | | Vehicle Condition | Lubrication |
| variation engine oil life | Oil life variation in that day. | % | Positive | | Vehicle Condition | Lubrication |
| mean oil pressure | Mean oil pressure | Pa | Positive | | Vehicle Condition | Lubrication |
| mean engine cool temp | Mean temperature reached by the coolant. Overheating worserns mileage | ºC | Positive | | Vehicle Condition | Other |
| variation mean coolant level | Variation of the coolant level in a day. Low coolant level may worsen mileage. If the coolant level is too low, the engine may overheat and suffer damage. | % | Positive | | Vehicle Condition | Other |
| duration with water in fuel light on | Time driving with water in fuel light on. More driving time with water light on may indirectly imply more fuel consumption | hours | Positive | Yes | Vehicle Condition | Other |
| duration engine hot light on | Time driving with engine hot light on. Engine's hot light lead to lubrication-related fuel excesses or engine's malfunctions | hours | Positive | Yes | Vehicle Condition | Other |
| mean engine cool temp | Time driving with clean exhaust filter light on. Issues with fuel filter may impact in fuel usage | hours | Positive | | Vehicle Condition | Other |
| variation fuel exhaust fluid | Variation on the DEF (Diesel Exhaust Fluid) in the day. Fuel economy is better when using DEF | % | Positive | | Vehicle Condition | Other |
| variation fuel filter life | Variation of engine's fuel filter. Short fuel life remaining may cause more fuel usage | % | Positive | | Vehicle Condition | Other |
| distance with malfunction indicator lamp (MIL) on | Distance traveled with MIL on. More distance, more fuel consumption (since the vehicle is driving with potential issues) | meters | Positive | Yes | Vehicle Condition | Other |
| total odometer | Maximum value of the odometer. A way to indicate that a vehicle is old. The higher the value, the worst the mileage may be | m | Positive | | Vehicle Condition | Other |
| mean tire pressure fl | Mean value of the wheel's pressure (front-left) | Pa | Negative | | Vehicle Condition | Tyres |
| mean tire pressure rl | Mean value of the wheel's pressure (real-left) | Pa | Negative | | Vehicle Condition | Tyres |
| mean tire pressure fr | Mean value of the wheel's pressure (front-right) | Pa | Negative | | Vehicle Condition | Tyres |
| mean tire pressure rr | Mean value of the wheel's pressure (rear-right) | Pa | Negative | | Vehicle Condition | Tyres |
| mean exterior temp | Mean value of the exterior temperature. Very low temparatures may worsen mileage | ºC | Negative | | Weather Conditions | Ambient Temperature |
| duration driving with T>0 and T<=20 | Time while driving with a temperature between 0 and 20 ºC | hours | Positive | Yes | Weather Conditions | Ambient Temperature |
| duration driving with T>-20 and T<=0 | Time while driving with a temperature between -20 and 0 ºC | hours | Positive | Yes | Weather Conditions | Ambient Temperature |
| duration driving with T<=-20 | Time while driving with a temperature below -20 ºC | hours | Positive | Yes | Weather Conditions | Ambient Temperature |
| duration raining | Time with windshields on (hours), assuming that it corresponds to raining time. Higher time may lead to higher consumption (road difficulties) | hours | Positive | Yes | Weather Conditions | Rain |

**TABLE 11** Features used for predicting the fuel usage, with their associated categories and subcategories, according to [5] for Operational Mass, Road Conditions, Vehicle Conditions and Weather Conditions