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FORECAST AND ANALYSIS OF THE PORTUGUESE CAR FLEET AND AUTOMOTIVE AFTERMARKET USING TIME-SERIES MODELLING

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Abstract

The car fleet size and composition have a direct impact on the automotive aftermarket business value. This study used Time-series models to forecast the Portuguese car fleet composition until 2030, which is projected to rise by just 2% (6.3 million vehicles). It is highlighted the exponential growth of EVs reaching a 12.2% fleet share by 2030, under a Neutral scenario. The car fleet composition was adjusted under three scenarios after external conditioning variables such as environmental policies and the introduction of shared cars were factored in, affecting the automotive aftermarket value. While it is expected to increase from 914.2 to 950.7 million euros between 2018 and 2030, the maintenance market share of internal combustion engine vehicles is expected to decrease. On the other hand, next-generation vehicles such as EVs, shared cars, and partially automated cars, are projected to take a growing share of the car fleet and automotive aftermarket value of the future.

Keywords: Forecasting models, Car fleet modelling, Time-series, ARIMA, Electric Vehicles, Automotive aftermarket.

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1. Introduction

What will be the main drivers in the evolution of the Portuguese automotive aftermarket? In 2018, the national automotive aftermarket was worth 914.2 million euros, and by 2030, it is projected to be worth about 950.7 million euros[1]. However, its future is uncertain, as it is dependent on the evolution of the car fleet composition as well as the associated maintenance costs. For example, the increasing adoption of Electric Vehicles[2], which is projected to reach a 12.2% fleet share (770,251 out of 6,310,690 vehicles) in Portugal by 2030, would have a negative impact on workshop business volume as EVs are manufactured with minor mechanical parts and require longer service intervals (Dombrowski et al., 2011). Furthermore, the emergence of next-generation mobility solutions such as shared cars and partially automated vehicles (estimated to be 1 million in 2030) suggests a different pattern of workshop maintenance operations. Additionally, the European Commission set a target of reducing CO2 emissions by 90% until 2050, transitioning to zero-emission vehicles to replace the internal combustion engine fleet (European Commission, 2020). Thus, internal combustion engine vehicles are doomed to be slowly phased out of the market due to the lack of compliance, decreasing 10% between 2018 and 2030. This paper intends to contribute to the evidence-based decision-making process in the automotive aftermarket as the abovementioned factors introduce threats such as a narrower range of car parts, different maintenance intervals, and more complex components and repairs. For instance, Tips4Y, the leading automotive intelligence company in Portugal that provides services to a significant share of Portuguese workshops and automobile retailers, is reliant on its customers' adaptation to the disruptive developments discussed in this paper. This study forecasts the segmented car fleet as well as the automotive aftermarket business value based on budgeted maintenance costs. It also aims

[1] Only considering maintenance operations in workshops that is the scope of the automotive aftermarket in this study.
[2] Throughout this paper, Electric Vehicles (EVs) refer to both Battery electric vehicles (BEVs) and Plug-in hybrid electric vehicles (PHEVs).

to provide insights into the requirements of different car segments in terms of specific maintenance operations. To forecast market entries, several Time-series models, namely ARIMA and Vector Auto Regression models, are developed. The 2030 vehicle stock is estimated through projected market entries and exits using a vehicle survival rate. Under Pessimistic, Neutral, and Optimistic scenarios, the forecasted car fleet composition and respective maintenance revenues are adjusted according to conditioning factors to account for the effects of exogenous variables. In a Neutral scenario, exogenous variables could result in a 6.4% decrease in the number of circulating vehicles in 2030, but the projected revenues could rise by 3.9% as a consequence of their effects in an Optimistic scenario. Is this a light of opportunity for the automotive aftermarket?

2. Literature Review

Forecasting the evolution of the automotive market is of great interest for governments, automobile manufacturers, aftermarket players, among others. Some key topics are the car fleet composition, usage patterns, and the substitution rate from conventional to next-generation vehicles. Concerning car fleet modelling, Jong et al. (2004) performed a comparison between car ownership models, including Time-series methods. In the last two decades, such models have been commonly used to forecast car fleets and other applications worldwide. Hence, by comprehending past observations, they can be described as future predictors (Ratnadip & Agrawal, 2013). Specific studies from authors that modelled and forecasted car fleets and related topics are mentioned in table 1. The literature is organized by the problem addressed, the methodology adopted, scope, data used, and results obtained.

Table 1 – Summary of studies of automotive modelling and forecasting initiatives

Author (s)	Problem/ scope	Methodology	Data	Results
1) Forecasting vehicle demand				
Chen (2011)	To forecast monthly vehicle demand in China.	ARIMA (*p*,*d*,*q*) model.	Historical vehicle monthly sales.	The model is suitable to forecast monthly vehicle demand.
2) Forecasting vehicle penetration rates				

Becker et al. (2009)	To forecast the market penetration of alternative fuel-powered vehicles in the USA.	Bass diffusion model in a lack of historical data situation.	Almost no historical data, estimation of *m*, *p*, and *q* parameters.	Electric Vehicle penetration rate of 64% in 2030.
Al-Alawi & Bradley (2012)	To compare penetration rate modelling studies from the past decades.	Statistical analysis of several studies' results.	Results of hundreds of studies.	The results of the models presented high variability.
3) Forecasting Electric Vehicle market share				
Silva & Moura (2016)	To forecast the diffusion and share of Electric Vehicles in Portugal.	System dynamics model: a combination of a Time-series model with a static disaggregate car-type choice model.	A combination of historical data and inputs as GDP, vehicle and energy costs, motorisation rate, vehicle and fuel technologies, mileage.	In the reference scenario, Battery Electric Vehicles will represent a 7.51% share of the total car fleet in 2030.
Rietmann & Lieven (2020)	To forecast the evolution of EV share and the impact of CO2 emissions in 26 countries.	Logistic growth model: a saturation limit of car inventories was predicted.	Historical data (yearly vehicle inventory of each segment per country).	EVs could reach a share of 36.2% in Portugal compared to a global 30% share in 2030.
4) Forecasting factors driving the adoption of Electric Vehicles and market share variability				
Xiang et al. (2017)	To forecast the adoption of Electric Vehicles and their main drivers in China.	System dynamics method introducing a feedback loop (e.g. EV sales influence the number of charging stations and vice versa).	Historical data integrating exogenous factors and their complex relationships through a causal loop.	With the development of technology, infrastructures and government policies, the adoption of EVs will scale.
Liu & Lin (2017)	The focus is to forecast the main factors responsible for EV market share variability in the USA.	Nested logit model with technology choices grouped into three classes (conventional cars, hydrogen fuel cell vehicles, and EVs).	Historical data that consists of technology choices. Some variables incorporated are technology risk, fuel and electricity price, vehicle price.	The main factors contributing to market share variability are energy cost, driving range limitation and charging availability.
5) Projecting the car fleet composition/ aftermarket				
Fridstrøm et al. (2016)	To project the composition of the future car fleet (by gross weight and fuel type), with a focus on EVs in Norway.	Stock-flow cohort model: new car registrations follow a discrete choice model based on purchase historical data.	Historical data (new registrations, scrapping, second hand, imported and exported cars).	Hybrid and Battery Electric Vehicle share of 50% of the youngest car fleet and 21% of the total fleet in 2030.
Laborda & Moral (2020)	To forecast the car fleet composition and automotive aftermarket volume in Spain.	Regression and ARIMA models to quantify and forecast variables, respectively.	Historical data (car registrations, mobility, number of accidents, car fleet, number of repairs) and exogenous conditioning factors.	The car fleet in 2030 will be disrupted by next-generation cars that will reshape the aftermarket business model.

1) The ARIMA model (Auto Regressive Integrated Moving Average) is one of the most widely used in car fleet modelling. For instance, Chen (2011) used it to predict the monthly vehicle demand in China.

2) Becker et al. (2009), and Mabit & Fosgerau (2011), used the Bass diffusion model to forecast the market penetration of alternative fuel-powered vehicles due to its suitability for forecasting the market penetration of early-stage products with network externalities, predicting the development of market acceptance already in progress. Thus, three parameters were estimated: the potential market size (m), the percentage of initial buyers whose intention to buy is not influenced by others (p), and the percentage of buyers who are likely to purchase after being influenced by others (q). On a broader spectrum, Al-Alawi & Bradley (2012) presented a detailed literature review of PHEV[3] and BEV[4] penetration rate modelling studies, including Bass diffusion models. These types of models are classified as easy to develop and can fit historical car sales patterns. However, there are drawbacks such as not including competition of other car segments in the model and the timing of peak sales needs to be defined in advance.

3) On a different perspective, Silva & Moura (2016) and Rietmann & Lieven (2020) forecasted the market share of EVs in Portugal by 2030. The authors used different methodologies and obtained distinct results as seen in table 1, with the most recent study presenting more optimistic results, which are likely due to the recent exponential growth of EV entries being taken into account. Silva & Moura (2016) used a system dynamics model to simulate purchasing behaviour under three scenarios of transportation policies, capturing the interrelationships among the system's drivers. Using a logistic growth model, Rietmann & Lieven (2020) forecasted the evolution of the EV inventory and its effect on global CO2 emissions for 26 countries. A saturation limit of car inventories was therefore predicted using historical data of each country. Secondly, the saturation limit was used to estimate a logistic growth function for each region, which was then modified based on annual vehicle sales projections.

4) Besides analysing the market share projections, it is important to discuss the key drivers of EV adoption as well as market share variability. To forecast the adoption of EVs, Xiang et al.

[3] Plug-in hybrid electric vehicles.
[4] Battery electric vehicles.

(2017) introduced a system dynamics method. The novelty of this method is the feedback system explained in table 1. Liu & Lin (2017) conducted a nested logit model to explain market share variability. The choice among successive nests is a logit function of the respective generalised costs used to calculate vehicle sales, car stock and segments' market shares.

5) Finally, Fridstrøm et al. (2016) projected the composition of the Norwegian car fleet using a stock-flow cohort model. The car stock of each segment is therefore calculated considering new registrations, scrapping, second hand, imported and exported cars. Recently, Laborda & Moral (2020) attempted to forecast the Spanish automotive aftermarket revenues under the actual transformation scenario. The study is divided into three main steps: firstly, the authors use regression models to estimate the main automotive variables that will affect aftermarket revenue forecasts over the long-term; secondly, these variables are forecasted until 2030 with ARIMA models; and thirdly, they attempt to quantify the impact of conditioning factors (e.g. legal and environmental policies, and the rise of next-generation cars), via participatory methods involving the automotive aftermarket stakeholders' perceptions. These conditioning factors were used to adjust both the car fleet size and revenues. For instance, pollutant cars that do not comply with regulations will be phased out under legal and environmental policies.

3. Methodology

To forecast the Portuguese car fleet and automotive aftermarket value in 2030, the following steps were followed: data gathering in the automotive industry, segmentation of the Portuguese car fleet to obtain its decomposition over time, annual vehicle market entries and exits projections, calculation of the annual vehicle stock, adjustments to the car fleet size according to conditioning factors, and computation of the expected car maintenance business volume.

Data gathering concerned mainly with collecting data to get access to an overview of the historical Portuguese car fleet, namely its maintenance costs. Thus, Tips4Y allowed access to a dataset containing 990 vehicles characterised by Plate_Year, Build_Year, Make, Cubic_Capacity, Fuel_Type, among other factors. Variables like mileage and maintenance costs were missing. Hence, the mileage had to be inferred from a study performed by Observatório ACP (2018) that estimates the average cumulative kilometres per vehicle by age (Appendix 1). Maintenance costs had to be retrieved from the Vehicle Running Costs platform (VRC)[5] which are calculated based on maintenance schedules of car manufacturers, including a labour cost of 37€/h (default value) and the cost of maintenance & repair parts. Therefore, 990 vehicle plates were manually entered into the platform, selecting the age range, mileage, among other characteristics required. After excluding invalid values[6], the maintenance costs and the respective list of parts for 716 vehicles were obtained. The next step was to segment the car fleet, an important task to understand which variables have the most significant influence on maintenance costs, allowing a cost forecast per car segment. Hence, a Decision Tree using the SPSS statistical software was elaborated due to its ease of visual interpretation and suitability to identify relationships and segments in data (IBM, 2012). The CHAID (Chi-square Automatic Interaction Detector) growing method was chosen, among other alternatives, since it permits multiway splits in data whenever there are statistically significant chi-square tests in predictors' categories. Maintenance cost is set as the dependent variable and vehicle characteristics as independent variables[7]. Since there was only one Electric Vehicle observation in the dataset provided, it was excluded. Various trees were created, manipulating parameters like growth and tree depth limits, leaving the default statistical significance of 0.05. Then, the trees were compared, with statistical significance and business-related conceptual interpretations taken into account. However, because of the limited sample size, results seemed not to be as significant as expected since multiway splitting generated too small categories for

[5] VRC is a website belonging to Tips4y that allows searching for car plates to get the budgeted maintenance & repair costs of a specific car, retrieved by querying a database of 4,237,368 unique vehicles.
[6] One must note that only maintenance costs were considered since the platform only provided warn out verifications for repair operations such as batteries or front axle brakes, as their life expectancy is highly unpredictable.
[7] Cubic_Capacity, Fuel_Type, Gross_Weight, Vehicle_Type, Gear_Box, Category, Body_Style.

reliable analysis. Hence, the entire procedure was repeated with 820 additional vehicles from a new dataset provided by Tips4Y[8]. After removing invalid values and outliers, the final sample size used in the segmentation process was 1243 vehicles. The selected tree comprising the variables Cubic_Capacity, Fuel_Type, and Vehicle_Type, yielded nine segments, excluding Electric Vehicles that would constitute the 10th segment, retrieved from an ACAP[9] dataset containing the annual aggregated cars entering the market per fuel type, from 2010 to 2019. Using Python, segments' criteria were applied in the database with 4,237,368 vehicles, significant of the Portuguese car fleet. A car must have been queried at least once in the VRC platform by a workshop or retailer to be included in this database. The output table with the aggregated number of market entries per segment and plate year, i.e., the year the vehicle entered the market, from 1990 to 2019, represented a proxy for the historical vehicle entries per segment. In order to forecast annual vehicle entries from 2019[10] to 2030, ARIMA models were used in the first attempt, considering the availability of enough historical data, fair accuracy levels (Chambers et al.), and capacity to deal with non-stationary series (Adhikari & Agrawal, 2013). This model is represented by equation (1) which uses lags in the historical data and forecasted errors to infer trends and render future projections (Adhikari & Agrawal, 2013). $\hat{Y}_i$ corresponds to the estimated car entries of segment *i* at time *t*, y_{t-p} represents entries in previous periods, α is the constant of the model, ϵ_t is the error at time *t*, β_i and Φ_i correspond to the coefficients, while *p* and *q* are the parameters of the model:

$$\hat{y}_{it} = \alpha_i + \beta_{i1} y_{it-1} + \ldots + \beta_{ip} y_{it-p} - \Phi_{i1} \epsilon_{it-1} - \ldots - \Phi_{iq} \epsilon_{it-q}, \quad i = 1,\ldots,10 \tag{1}$$

The role of assessing the series' stationarity is critical. A non-stationary series is rendered stationary in ARIMA models by applying finite differencing, stabilizing the mean, and

[8] One must note that EVs were excluded once again in the new dataset because they were under-represented.
[9] Associação do Comércio Automóvel de Portugal.
[10] Market entries for 2019 and 2020 had to be forecasted since the number of entries in this database for 2019, represented only 35% of the official market entries and the observations for 2020 corresponded only to the first couple of months. In contrast, the represented fleet in this dataset was, on average, 54% of the official Portuguese fleet from 2010 to 2018 (PORDATA, 2020). The under-representation in 2019 can be explained by the fact that cars from 2019 are expected to require a maintenance trip to a workshop 2 years after entering the market or between 15,000 and 30,000 km, and thus not having been queried yet.

eliminating the trend of the series (Adhikari & Agrawal, 2013). Hence, Dickey-Fuller and Phillips-Perron Unit Root tests were run in SPSS to assess the stationarity of each segment's series. Whenever a series presented to be non-stationary, differencing, represented by the parameter *d*, was applied to reach stationarity up to the second-order. Less often, but whenever necessary, the natural logarithm and square root techniques were applied to stabilise the series' variance. If the series were already stationary, no differencing was applied, and therefore *d* took the value of 0. After reaching stationarity in all segments, identifying the number of the Auto Regressive terms (*p*) and lagged forecasted errors, represented as the Moving Average (*q*) parameter, autocorrelations and partial autocorrelations analysis were performed. Individual ARIMA models with the appropriate parameters were then run in SPSS for each segment. For the 10^{th} segment composed by EVs, a Holt-Brown's Linear Exponential Smoothing model was also developed to smooth the ARIMA model's long-term exponential growth of Electric Vehicle entries, which was heavily influenced by its recent exponential proliferation.

Some authors, as stated in the literature review, attempted to build more robust and dynamic models, mainly to include external variables such as macroeconomic variables. Therefore, several VAR (Vector Auto Regression) models were developed to forecast segment entries to assess potential intricacies between segments, as well as to forecast Electric Vehicle entries with the inclusion of exogenous variables instead of relying solely on historical data. The VAR is a multivariate Time-series model that regresses a vector of multiple variables based on past observations (lags) of those same variables (Becketti, 2013). The Time-series vector for each segment was determined based on lagged (past) observations of the other segments, using the historical entries of each segment, including Electric Vehicles. The stationarity results previously obtained for the ARIMA models as well as the necessary differencing levels were considered. Before running the VAR model, the exogenous variables[11] had to be forecasted as

[11] List of exogenous variables tested: Real GDP growth YoY (PORDATA, 2021 and IMF, 2021), Consumer Price Index growth YoY, Electricity price, Diesel price, Petrol95 price, EV battery pack costs, Number of EV charging infrastructures.

a required input. This time, despite the model's good fit to forecast entries and the statistical significance of some exogenous variables, the results were unreliable, as discussed in the "Analysis and Results" section. As a result, as shown in the same section, the selected ARIMA and Holt-Brown's Linear Exponential Smoothing models were considered to be the most suitable and accurate options for forecasting vehicle entries.

Finally, vehicle market exits per segment had to be calculated. Thus, based on the study of Fridstrøm et al. (2016), an average survival rate was computed for cars with ages between 0 and 40 years (Appendix 2). This rate considers vehicle deregistration and scrappages. One must note that due to the lack of data on the survival rate of cars older than 30 years, a constant rate was assumed. As an assumption, no car exits the market in the same year it enters. Thus, in year 0, there are no market exits. Therefore, the expression (2) was used to calculate the number of vehicle exits for segment *i* at any moment, *t* years after the first instant[12], where *j* represents the vehicle age and S is the survival rate of any vehicle with *j* years of age:

$$\text{Vehicle Exits}_i\,(t) = \sum_{j=1}^{t} \text{Vehicle Entries}_{j\text{-}1} \times (1\text{-}S_{t\text{-}j\text{+}1}),\ \ i = 1,\ldots,10 \tag{2}$$

The cumulative market entries and exits allowed to calculate the annual car stock per segment until 2030. Additionally, exogenous conditioning factors including legal and environmental policies, shared cars, and vehicles with Advanced Driver-Assistance Systems (ADAS) level 3[13] were applied to simulate the impact on the future car fleet composition under three scenarios.

With the maintenance costs retrieved from the Decision Tree, the next step was to estimate the automotive aftermarket business volume. Since budgeted maintenance costs for the Electric Vehicle segment were unavailable, it was benchmarked from three studies that estimated how much less this segment costs on average than an internal combustion engine vehicle. Propfe et al. (2012), Propfe et al. (2013), and Weldon et al. (2018) considered a 50%, 26.5%, and 18%

[12] The first instant corresponds to 1990 which was the furthest year included to forecast market entries.
[13] ADAS level 3 is a conditional automation system that allows vehicles to be in full control of the driving process under certain conditions, still requiring a driver to take control when needed (Mehta et al., 2020).

reduction, respectively. Therefore, to decrease the margin of error, the assumed rate in this study was their average, 31.5%. The average maintenance cost for internal combustion engine vehicles, retrieved from the Decision Tree, was reduced by 31.5% to compute the Electric Vehicle segment's maintenance cost. The same method was adopted to calculate the maintenance costs of shared cars and vehicles with ADAS level 3, considering an increase of 40% and 25%, respectively, when compared to the average costs of internal combustion engine vehicles and EVs (Laborda & Moral, 2020). Finally, an overview of the car segment requirements in terms of moving parts and maintenance specifications was performed.

4. Analysis and Results

As a result of the segmentation process used to determine the composition of the Portuguese car fleet, a Decision Tree was generated, identifying nine internal combustion engine vehicle (ICEV) segments differentiated by average maintenance costs, according to differences in the most significant dependent variables (Appendix 3). The algorithm categorized Fuel_Type, Cubic_Capacity, and Vehicle_Type as the best predictors of maintenance costs, then proceeded with significant splits until reaching nine terminal nodes that correspond to the segments described in table 2. Node 0 represents the entire sample of internal combustion vehicles in the Decision Tree displayed in Appendix 3. The first split considers Fuel_Type as the most relevant variable in explaining differences in maintenance costs, concluding that, in general, Diesel cars are more expensive to maintain than Petrol/ internal combustion hybrid cars, costing on average 309 and 251 euros per workshop maintenance visit, respectively. The second-best predictor is Cubic_Capacity. The norm is that higher cubic capacity engines have greater maintenance costs among Petrol cars but this is not always the case for Diesel cars (table 2). The cheapest segments are both Diesel and Petrol cars with the smallest cubic capacities. These vehicles are mainly light-duty hatchbacks, which aligns with Monteiro's (2020) findings that show that the lighter the weight, the lower the maintenance costs. On the other hand, Diesel cars with 1689 cc. or more are among the most expensive segments to maintain. These are mostly large, heavy cars like sedans, vans, and SUVs. Further statistically significant differences were found in Vehicle_Type for cc. engines between 1422-1499 as well as 1500-1689, splitting the data into four terminal nodes. The average cost of a commercial vehicle with a 1422-1499 cc. engine is 486 euros, more than double of a medium-sized Diesel engine commercial vehicle. According to Tips4y, a possible explanation for this disparity is that small/ medium engines have shorter maintenance intervals, which, when combined with a greater usage rate associated with commercial vehicles, results in much higher maintenance costs. Nine different segments were selected after analysing and validating the Decision Tree with Tips4y, as shown in the table below. Vehicle parts account for 69% of the total costs. A 10th segment made up of Electric Vehicles was added since there were no observations for the segmentation process.

Table 2 - Overview of the segments retrieved from the Decision Tree

Segment	Cubic Capacity	Fuel Type	Vehicle Type	Tree Node	Average Total Cost (€)	Average Parts Cost (€)	Average Labour Cost (€)
1	≤1389	Diesel	-	3	224.74	161.70	63.04
2	]1389,1422]	Diesel	-	4	292.47	198.47	94.00
3	]1422,1499]	Diesel	Passenger	10	340.48	238.70	101.78
4	]1422,1499]	Diesel	Commercial	11	485.70	337.71	147.99
5	]1499,1689]	Diesel	Passenger	12	283.29	196.57	86.73
6	]1499,1689]	Diesel	Commercial	13	229.42	146.08	83.33
7	>1689	Diesel	-	7	328.73	236.57	92.21
8	≤1124	Petrol/Hyb.	-	8	207.93	134.33	73.60
9	>1124	Petrol/Hyb.	-	9	269.40	180.17	89.23
10	-	Electric	-	-	202.62	-	-

The segments are described by Cubic_Capacity, Fuel_Type, and Vehicle_Type. There are seven different cubic capacity ranges, three main fuel categories, and two vehicle types. It is also displayed the respective segment's terminal node as well as a breakdown of the average maintenance costs. For the 10th segment, the only characteristic available is the fuel type since observations were retrieved from a dataset with aggregated entries with no other characteristics (ACAP, 2020).

Following that, the annual historical entries per segment were forecasted with ARIMA (p,d,q) modelling. Dickey-Fuller and Phillips-Perron Unit Root tests were run individually to assess the stationarity of segments, where every segment rejected the null hypothesis for stationarity (Appendix 4) since the p-values were always much greater than 0.05. Thus, after testing various differencing values and graphical analysis of each serie's trend, every segment required 1 or 2 differencing levels to become stationary. To stabilise the serie's variance of segments 6 and 7, the natural logarithm and square root transformations were used, respectively. Thereafter, several models were run and compared in terms of fit and statistical significance, testing different AR (*p*) and MA (*d*) parameter values for the required differencing. The selected models are listed in the table below, along with their statistics.

Table 3 - Overview of the selected ARIMA (*p*,*d*,*q*) models

Segment	Model	Constant	Log/ Sq. root	R-squared	Ljung-Box test	BIC	AR *p*-value	MA *p*-value
1	(0,2,1)	No	No	0.785	0.905	16.450	-	0.000
2	(1,1,2)	No	No	0.837	0.884	15.845	0.047	0.004; 0.023
3	(0,2,1)	No	No	0.859	0.409	16.546	-	0.000
4	(0,1,2)	No	No	0.787	0.434	15.581	-	0.070; 0.065
5	(1,2,0)	No	No	0.640	0.544	18.013	0.010	-
6	(0,1,1)	No	Log	0.704	0.341	14.323	-	0.034
7	(2,1,1)	No	Sq. root	0.869	0.455	18.964	0.011; 0.020	0.021
8	(1,2,0)	No	No	0.747	0.208	16.204	0.044	-
9	(2,1,1)	No	No	0.882	0.507	18.184	0.010; 0.009	0.003
10	(0,2,0)	Yes	No	0.971	-	13.585	-	-

The ARIMA models selected to forecast market entries contain three components (*p*,*d*,*q*), an eventual constant, and the possibility of a natural logarithm or square root transformations. The model selection criteria are based on the statistical significance of the AR and MA parameters as well as the R-squared, Ljung-Box test, and BIC results. The reasonability of the predictions is not displayed, however, it is also considered for model selection.

Regarding parameter *d*, half of the models required second-order differencing, meaning that the series were differenced twice, whenever the first-order was not enough to reach stationarity. Additionally, half of the models required 0 terms of Auto Regression, indicating that forecasted values are not related to past lags. Segments 7 and 9 required an AR of 2, implying that estimates for a given year are not only based on observations from the previous year, as in segments 2, 5, and 8, but also on *t*-2. The most common *q* parameter is 1, which indicates that the error of the series *t* is based on the error values observed in *t*-1 (Adhikari & Agrawal, 2013). The models presented fit statistics as well as statistically significant AR and MA parameters in general. In terms of the R-squared parameter, all models had high values for explaining the variance in the series, ranging from 0.63 to 0.97. The models with *p* greater or equal than 1 had statistically significant AR parameters at a 95% level of confidence (α = 0.05). As for the Moving Average parameter, segment 4 shows that both MA *p*-values (0.070; 0.065) are not statistically significant (indicating lack of evidence that both parameters are different from zero), although close to 0.05. Nevertheless, the model was kept since the series "passed" in the fitness tests and did not provide unrealistic results. Every model performed well in the Ljung-Box test which checks the randomness of the errors, displaying *p*-values well above 0.05. Hence, every segment failed to reject the null hypothesis that states that data has an independent distribution, which is a positive outcome since the model does not show a lack of fit. The Bayesian Information Criterion (BIC) was used as the final test to determine which model had the best fit by comparing models for the same segment and penalizing those with more parameters due to overfitting. Overall, the values were low, suggesting no overfitting issues. Additionally, the EV segment required special attention as it is an early-stage segment in Portugal, with only ten years of historical entries, bringing uncertainty to forecasts. Thereafter, the Holt-Brown's Linear Exponential Smoothing model revealed significance to simulate a conservative scenario that smooths out the influence of EVs' recent exponential proliferation (Appendix 5.1), in case the ARIMA's assumed exponential growth does not materialize (Appendix 5.2). This model presented an R-squared of 0.96, an α parameter with a *p*-value of 0.000, and no data transformation. Therefore, it was accepted as a good fit model with a reasonable Pessimistic scenario for EV diffusion by assuming linear growth, reaching 465,304 entries in 2030. The ARIMA model produced comparatively more realistic results by projecting 623,937 entries in 2030, as recent literature points towards a sustained exponential adoption.

Finally, although the previous models were statistically significant in forecasting vehicle entries per segment as displayed in Appendix 6, it was pertinent to test a more sophisticated model to assess causalities between segments as well as the impact of exogenous variables. Several VAR models were tested in this way, however, they performed worse than ARIMA. Although the selected VAR model revealed a good fit for forecasting market entries since the equations for all segments disclosed statistical significance (average R-squared of 0.93 and all *p*-values equal to 0.000), results were unrealistic. Perhaps, by not imposing a restriction, the model estimated negative entries that are truncated in the simulation in six out of seven Diesel segments from 2020, 2021 or 2022, assuming an unrealistic premature Diesel extinction. The model regresses the Time-series for each segment built on the causalities with other segments, so the results' reliability is dependent on whether or not causalities between segments are statistically significant (Becketti, 2013). Hence, the Granger Causality Wald test was run, which revealed that there are no statistically significant causalities between segments in the majority of cases, resulting in poor results. Additionally, an individual VAR model to forecast EVs incorporating exogenous variables had a great fit, including the number of charging infrastructures available (Appendix 7) and EV battery costs (Appendix 8) as statistically significant exogenous variables. However, the results were unrealistic once again as the forecasted cumulative EV entries were 2.6 million, well above the literature projections. Overall, the forecasts' standard errors were high which explains the models' lack of significance. Moreover, the forecasted exponential growth of both exogenous variables might be driving an overly optimistic prediction. In the end, ARIMA models were found to be the most suitable to forecast the car fleet. Therefore, figure 1 depicts the evolution of the aggregated annual entries and exits in Portugal over time.

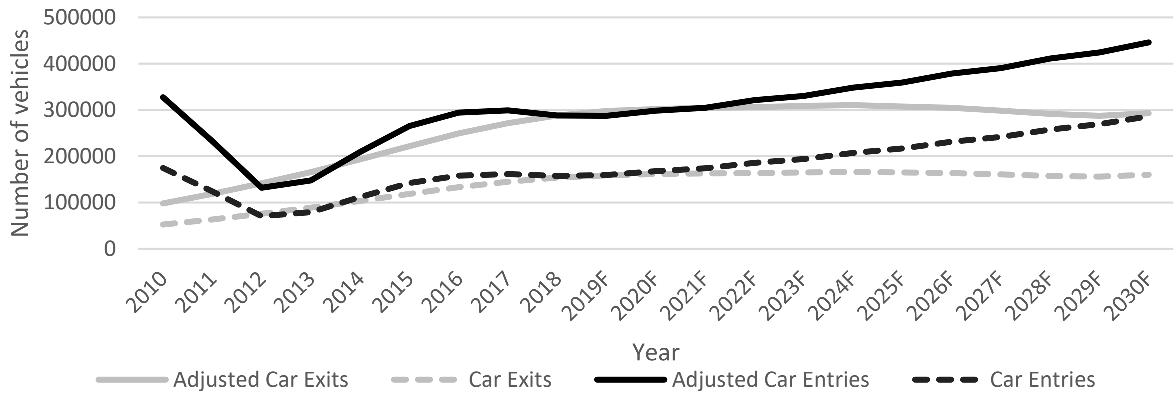

Figure 1 – Evolution of the aggregated vehicle entries and exits from 2010 to 2030

Figure 1 depicts the evolution of both car fleet entries and exits in Portugal, over 20 years (2010-2030), including forecasts (labelled with "F"). Values were adjusted using a proportionality factor to solve the under-representation issue.

Figure 1 shows that car entries fell by 60% between 2010 and 2012, coinciding with the financial crisis in Portugal. It took four years for annual entries to recover significantly, with a plateau in 2016-2017 and a predicted slight drop from 2018 to 2020, before climbing again. This slight drop might be due to the fact that new cars entering the market in 2018 are most likely queried in the VRC platform every two years or 15,000-30,000 kilometres, depending on manufacturers' advice. Since the available database only contains observations up to the middle of 2020 and must be queried at least once, there is the possibility of a minor under-representation of cars from 2018. In fact, car entries accounted for only 43% of all official entries in Portugal in 2018 (PORDATA, 2020). From 2010 to 2018, annual entries were consistently under-represented, accounting for 53% on average of the total official number.

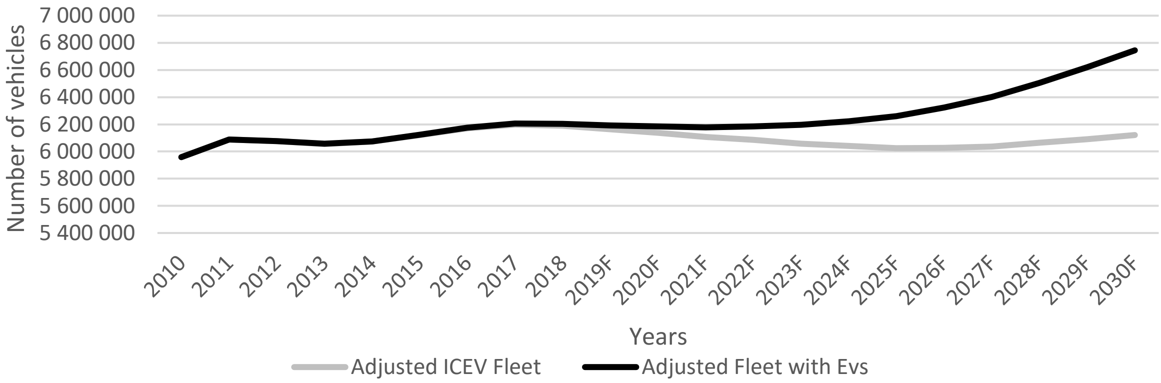

Figure 2 – Adjusted Portuguese aggregated car fleet evolution from 2010 to 2030

Figure 2 shows the evolution of both historical and forecasted total car fleet size in Portugal for over 20 years. The values are adjusted with a proportionality factor based on the official historical Portuguese fleet size.

Annual car entries and exits had to be adjusted using the 53% proportionality factor in both the historical and forecasted periods, as shown in figure 1. Consequently, the annual car fleet stock was also under-represented, accounting for 47% of the total Portuguese car fleet on average (PORDATA, 2020). As a result, the annual total car fleet, as shown in figure 2, was subjected to the same proportionality factor procedure. Because the same correction factor was used every year, this technique did not affect the series' trend. In terms of the aggregated fleet, the growth rate began to be positive in 2013 and remained positive until 2018-2023, when it reached a plateau. This growth coincided with Portugal's recovery from the financial crisis, with real GDP growth (YoY) increasing from -0.9% in 2013 to 3.5% in 2017, before beginning to decline until 2020 (PORDATA, 2020). Because car entries and exits are set to be nearly equal, a plateau until 2023 succeeds. From 2023 to 2030, the car fleet is expected to grow at a 1.3% annual average rate, from 6,196,695 to 6,744,833 vehicles. The Electric Vehicle segment is the primary driver of this growth, as shown in figure 2, where the decline in internal combustion engine vehicles is offset by an annual average increase of 24.1% in Electric Vehicle stock over the same period in a Neutral scenario. The results appear to be realistic, as increasing adoption of Electric Vehicles might cannibalise internal combustion engine vehicle entries.

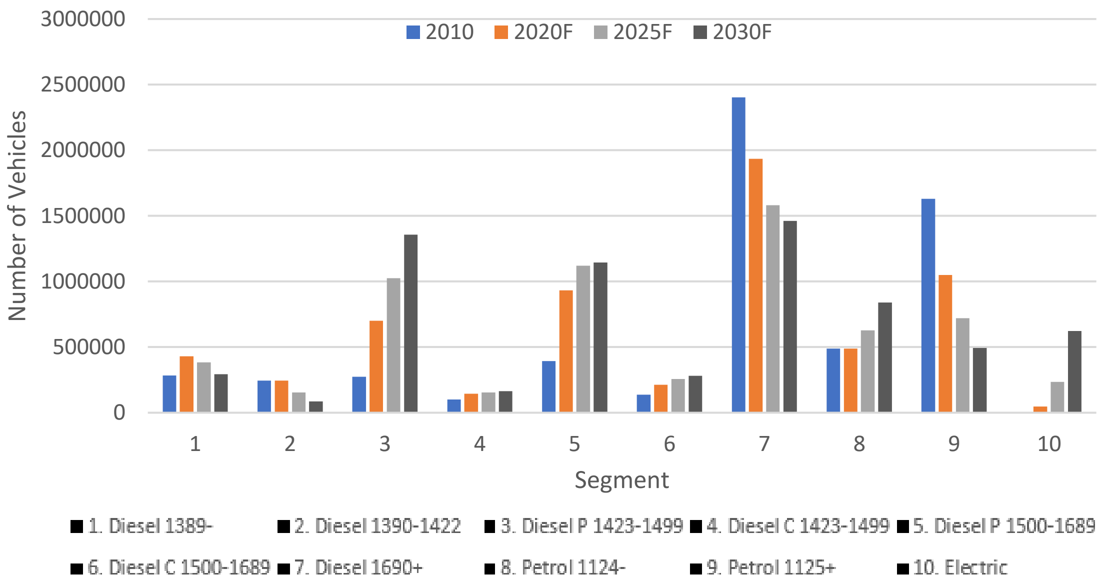

Figure 3 – Evolution of the car fleet size per segment between 2010 and 2030

Figure 3 presents the evolution of the Portuguese car fleet size per segment in 4 periods of time (2010, 2020, 2025, 2030). The last 3 periods result from ARIMA forecasts. Appendix 10 shows a detailed annual evolution.

Figure 3 shows the evolution of the car fleet size per segment over a 20-year period. At first glance, there appear to be two possible trade-offs between segments. On the low-cc. spectrum, Petrol cars with smaller engines are expected to gain share (segment 8), opposing a decrease in smaller Diesel engine cars (segments 1 and 2). After the crisis, the target consumers with presumed lower purchasing power may have been more sensitive to a 14% increase in Diesel prices until 2019, when the price difference between Diesel and Petrol shrank (Appendix 9). As a result, the higher cost of Diesel cars in these lower-tier segments may be a barrier to purchase. Commercial Diesel cars have a more stationary behaviour than other vehicle types. Cubic capacity-wise, commercial lower cc. cars (segment 4) almost stagnate, pointing to a possible transition to larger and more economical engines for commercial activities (segment 6).

Medium-sized Diesel engine cars (segment 3) are expected to rise, being the fastest-growing internal combustion engine segment. Between 2010 and 2020, the most significant increase was in segment 5, which is positioned in the middle of medium and large Diesel engines. However, it started to fall in entries since 2016, facing a fleet growth deceleration. Diesel-wise, this could indicate that consumers now prefer either medium-low or large engines. Segment 7, represented by large Diesel engine cars, is worth highlighting because it has by far the highest share over the 20-year period studied. Between the 1990s and the early 2000s, big Diesel engine cars were the most popular, accounting for half of all car entries in 2000. They have been gradually phased out since then, as they are linked to higher consumption, pollution, and maintenance costs. However, due to a recent consumer shift to SUVs and larger cars, it is expected to gain in popularity in the coming years (Voelk, 2020). Medium-large Petrol engine cars (segment 9) have the highest expected tumble from 2020 to 2030, indicating that among the Petrol options, bigger engines are becoming less popular, owing to higher fuel consumption and price. Finally, segment 10 is the most disruptive, since the stock of EVs grew from 166 to 28,551 between 2010 and 2019 and is expected to continue growing exponentially, accounting for 9.25% (623,937 vehicles) of the total Portuguese fleet by 2030 in a Neutral scenario. In a Pessimistic and Optimistic scenario[14], this share could range from 6.9% to 11.6%.

[14] The Pessimistic scenario considers the forecasts retrieved from the Holt-Brown's Linear Exponential Smoothing model, the Neutral considers the ones from the ARIMA model, and the Optimistic contains the share of the Neutral scenario plus the difference between the Neutral and Pessimistic shares.

Finally, as historical data alone is insufficient to make future projections in such a dynamic industry, based on the study of Laborda & Moral (2020)[15], the impact of exogenous conditioning factors is incorporated to adjust the future car fleet size, quantifying the impact of legal and environmental policies and the rise of shared cars as well as to adjust the car fleet composition reflecting the emergence of disruptive trends such as Advanced Driver-Assistance Systems (ADAS) level 3 cars, under three scenarios. In the Neutral scenario, legal and environmental policies, as well as the emergence of shared cars, are expected to shrink the car fleet by 7.1% and 2.4%, respectively. The second is expected to cannibalise sales of privately owned cars. Both factors add up to a significant reduction in the Portuguese car fleet of 595,371 vehicles (8.8%) in 2030, resulting in an adjusted total of 6,149,462 cars (Appendix 11).

Regarding the car fleet composition, shared cars entering the market are equal to the shrinkage it caused, simulating a replacement of internal combustion vehicles by shared cars. Since further research revealed that EVs are better suited for car sharing than internal combustion engines due to lower maintenance costs, all new shared cars were assumed to be electric (Mehta et al., 2020). In 2030, vehicles with ADAS level 3 are projected to weight 25.6% of the Spanish car fleet. However, according to the AVRI[16], Portugal does not rank among the top 30 countries in terms of autonomous vehicles readiness, with Spain ranking 22nd place (KMPG, 2020). Therefore, due to a lack of information regarding the acceptance of ADAS level 3 vehicles in Portugal, a conservative approach led to the estimation of half of the Spanish market share (12.8%). Table 4 summarises the evolution of the adjusted Portuguese fleet composition over time in three scenarios, highlighting the shrinking of internal combustion engine vehicles. On the other hand, the number of ADAS level 3 cars, shared cars, and EVs is increasing. In a Neutral scenario, the predicted share of Electric Vehicles in 2030 rises to 12.2%, including the

[15] This study was used to benchmark external impacts for the Portuguese automotive aftermarket sector since Spain is economic and culturally identical to Portugal.

[16] Autonomous Vehicles Readiness Index measures preparedness for autonomous vehicles country-wise, considering policy and legislation, technology and innovation, infrastructures, and consumer acceptance (KPMG, 2020).

electrified car sharing fleet share (Appendix 12). It is important to note that the emergence of new segments does not compensate for the decline in conventional internal combustion engine vehicles, as the car fleet after including the conditioning factors accounts for 93.6% of the total fleet when only historical data is used in 2030. When comparing the 2025 and 2030 Indexes calculated below, the trend shows that, in all scenarios, conditioning factors are expected to have an increasingly negative impact on the forecasted fleet size over time (Appendix 13).

Table 4 - Car fleet share per category after applying conditioning factors

	Pessimistic		Neutral		Optimistic	
	2025	2030	2025	2030	2025	2030
Total fleet without conditioning factors (M)	-	-	6260	6745	-	-
ICEVs non-partially assisted	91.9%	80.1%	89.5%	75.4%	86.8%	69.5%
ICEVs ADAS level 3	4.2%	10.7%	5.8%	12.4%	7.4%	14.2%
EVs shared cars	0.4%	1.4%	0.8%	2.6%	1.6%	4.9%
EVs ADAS level 3	0.1%	0.8%	0.2%	1.3%	0.3%	1.9%
EVs remaining	3.3%	7.0%	3.6%	8.4%	3.9%	9.6%
Total EVs	3.9%	9.2%	4.6%	12.2%	5.8%	16.4%
Total fleet with conditioning factors (M)	5907	5877	6084	6311	6172	6528
Index[17]	94.4%	87.1%	97.2%	93.6%	98.6%	96.8%

The total fleet without conditioning factors in 2018 is 6,204,657. Scenarios consider the severity of exogenous variables, where a Pessimistic scenario points towards a stronger negative impact of environmental policies in the total car fleet and a lower diffusion of next-generation segments such as shared cars and cars with ADAS level 3 technology. The Optimistic scenario considers the opposite, which is the scenario that could represent a larger fleet size.

Another relevant subject of this research is the distribution of specific maintenance and repair parts per segment. Regarding mandatory replaced parts in scheduled maintenance visits to workshops, the most replaced are engine oil, engine oil filter, and cabin filter, with a prevalence of 95.8%, 95.2%, and 67.9% per maintenance visit, respectively (Appendix 14). Both Diesel and Petrol cars with smaller cubic capacities (segments 1 and 8) have fewer scheduled replacements, which is understandable given that they are the two least profitable internal combustion engine cars in terms of maintenance costs. Medium-sized Diesel engines (segments 3 and 4) have the highest percentage of replacement operations, which is consistent with the

[17] Index = (Total fleet with conditioning factors/ Total fleet without conditioning factors).

results as they are the most expensive segments to maintain, respectively (Appendix 15). The hypothesis that Diesel cars with 1422-1499 cubic centimetre engines had shorter maintenance intervals and thus required more frequently replaced maintenance parts, was statistically validated. Regarding repair parts that are scheduled for verification, being replaced or not according to their condition, windshield wipers are by far the part with the most detrition, with a 94.2% verification rate of all maintenance operations (Appendix 16). The verification rate distribution does not differ significantly by segment, as expected (Appendix 17).

5. Discussion

The main factor to highlight from the previous results is the projected decline of internal combustion vehicles over time, in contrast to the emergence of new segments that are expected to gain significant market share by 2030. Segment 10, composed of EVs, seem to be the medium/ long-term option for sustainable zero-emission mobility with automakers being forced to switch Diesel and Petrol to electric or alternative fuels to comply with the European decarbonisation regulation (European Commission, 2020) that is represented by the legal and environmental policies in this study. In concordance with the VAR developed in this paper, Palmer et al. (2017) also found a strong link between the emergence of charging infrastructures available and the decline of battery ownership costs, with an increasing EV adoption. Electric charging points in Portugal are expected to continue to grow exponentially in the future (Appendix 7), opposing a downward trend of battery costs (Appendix 8). EVs are also expected to reach price parity with ICEVs (Woodward et al., 2020). As a result, the projected EV exponential growth can be justified based on the evolution of the main drivers for its adoption. Furthermore, other authors' findings should be compared to the forecasted 12.2% share of EVs in 2030, ranging between 9.2% and 16.4%, under a Pessimistic and Optimistic scenario. Silva & Moura (2016) and Rietmann & Lieven (2020) projected a 7.51% and 36.2% share of EVs in Portugal by 2030, respectively. The results of this study (12.2%) are in the middle of these authors' projections. Though, the first author adopted a conservative approach, probably due to having only five years of historical entries available, missing the recent exponential growth. As for the other disruptive segments, car sharing and ADAS level 3 are expected to account for 2.4% and 12.8% of the total car fleet in 2030, respectively, under a Neutral scenario. Car sharing options lead to a mobility shift that has been confirmed in recent years, with annual double-digit growth as people forego the cost of car ownership that are barely used (Deloitte, 2017).

Once forecasted the car fleet composition in 2030, managerial implications were assessed by measuring the automotive aftermarket volume from a maintenance perspective. Without accounting for the impact of the above-mentioned conditioning factors, the business volume for workshops is expected to increase from 914.2 to 967.9 million between 2018-2030, based on the average maintenance costs from the Decision Tree. Interestingly, consumers are shifting towards the most expensive Passenger cars to maintain (medium Diesel engines). Thus, this segment 3 will have the most significant increase in revenues, reaching 461.9 million euros in 2030, compared to 195.6 million in 2018. Large Diesel engines (7) and medium-large Diesel engines (5) are the other two most representative segments, with a combined share of 41.6% by 2030. However, large Diesel engines will face severe losses in the next 10 years due to their elimination from the market given that it is the most pollutant segment and with the highest purchase price. In terms of market value, lower Diesel engine segments (1 and 2) will decline, attaining very low importance for the automotive aftermarket value. Petrol-wise, higher cubic capacities will lose market share, while lower engines will gain, driven by variations in terms of the number of existing cars. Between 2018 and 2030, the EV segment's business volume will increase dramatically, rising from 3.2 to 126.4 million euros. The main growth driver is the exponential increase in the number of cars since EVs have fewer moving parts and require longer maintenance intervals, resulting in a lower maintenance cost per vehicle (Dombrowski et al., 2011). Should this segment continue to grow exponentially, the automotive aftermarket could face losses as the average maintenance cost per vehicle would fall. Appendix 18 contains a summary of the evolution of the business volume share per segment over time.

In the last instance, the impact of conditioning factors on the automotive aftermarket business volume must be addressed, not only because of fleet size adjustments but also because shared cars and ADAS level 3 imply higher maintenance costs than the average internal combustion vehicles by 40% and 25% (Appendix 19)[18], respectively, due to shorter maintenance intervals and more complex systems (Laborda & Moral, 2020). Hence, considering the new fleet composition after applying the conditioning factors displayed in table 4, the internal combustion vehicle market value is expected to shrink 87.3 million euros in 2030 due to the combined impact of legal and environmental policies and car sharing, under a Neutral scenario. Moreover, considering the emergence of the electric car sharing fleet, the adjusted market value for EVs in 2030 is 205.8 million euros (adjusted volume share evolution in Appendix 20). Results show that the increase in value addressed by ADAS level 3 and shared cars can compensate for the negative impacts caused by the legal and environmental policies, internal combustion vehicle market decline, as well as the lower maintenance costs imposed by EVs. Appendix 21 contains the breakdown of the aftermarket volume by car fleet category, highlighting 950.7 million euros as the total market value after applying the conditioning factors, by 2030, under a Neutral scenario. The indexes calculated in Appendix 21 show that despite a diminishment in the forecasted number of existing cars after applying the conditioning factors, the remaining vehicles represent a higher average business volume over time that can represent a 3.9% increase in the overall market value, by 2030, under an Optimistic scenario.

A final recommendation for managers is that there is an opportunity to remain competitive and increase profits in the long-term. This is plausible if workshops acquire the expertise to perform

[18] ADAS level 3 cars possess expensive sensor technology to maintain (Heid & Kempf, 2018) and shared cars require shorter maintenance intervals as the daily utilization rate can reach 50%, compared with 4% for a privately owned car (Mehta et al., 2020). A 40% and 25% increments were applied over the average maintenance cost retrieved from the Decision Tree for the ICEV fleet (295.8 euros). For EVs, increments were applied over their average maintenance cost of 202.6 euros.

maintenance operations in fast-growing segments with complex electric and technological systems such as EVs and ADAS level 3, rather than focusing only on conventional combustion vehicle mechanical operations, which are simpler but targeted to a declining segment.

6. Limitations and Recommendations

Naturally, a series of limitations arose. Although the forecasted market entries using the ARIMA model presented statistically significant results, this kind of model has flaws. Thus, statistically significant causalities between segments may be overlooked, as it is not possible to incorporate competition among segments in ARIMA simulations. Also, the expected negative impact of Covid-19 in the automotive sector was not considered as a result of the unavailability of data regarding its evolution. Moreover, due to the lack of data on historical entries of shared cars and ADAS level 3 cars in Portugal, their projected market share and impact on the next decade total fleet had to be benchmarked rather than measured empirically. Further research should be done on this subject when there is enough historical data accessible.

The process of retrieving the costs from the VRC platform was manually run. As a consequence, even though outliers were removed, the findings are susceptible to human error. In addition, assumptions had to be made to estimate EV, shared car, and ADAS level 3 maintenance costs. In future research, authors are challenged to dedicate a study to empirically estimate their costs, for instance, by interviewing manufacturers and fleet managers, and therefore including these observations in the segmentation process. For the aftermarket volume estimation, only the budgeted maintenance costs were considered since the repair parts replacement timing is highly unpredictable. Further studies involving the actual replacement of relevant moving parts, such as batteries or front axle brake pads, described in Appendix 16, may, for example, be established using participatory methods with workshops in order to attempt the estimation of their replacement probability, and thus computing the expected volume for repair operations[19].

[19] Repair services correspond to around 50% of workshop revenues in Portugal.

The most significant limitation was the lack of access to the official vehicle annual entries as our database only contained cars that had to be queried in the VRC platform previously. This suggests that some cars might have left the market or even not visited a workshop nor being queried, during the period studied. Hence, future researchers are recommended to try to get access to a database containing the official vehicle registrations in some way.

7. Conclusion

This study analysed the evolution of the Portuguese automotive aftermarket as a product of changes in the car fleet composition. The Portuguese car fleet was forecasted using univariate and multivariate Time-series models after an innovative segmentation method. Results revealed potential trade-offs between segments, highlighting the historical and forecasted exponential growth of Electric Vehicles that might reach a 12.2% fleet share in 2030, becoming the fastest-growing segment in both periods. Since the univariate model predictions were based solely on historical data, the results were adjusted accounting for external factors that are expected to impact the automotive aftermarket in the near future. Adjusted results indicate a decline in internal combustion engine vehicles over time, as a result of legal and environmental policies as well as the emergence of mobility alternatives such as car sharing. Next-generation vehicles, as ADAS level 3 and electric shared cars, on the other hand, are expected to grow in popularity, gaining a significant share of the total car fleet by 2030 and beyond. Managerial implications were also assessed in terms of changes in the car fleet composition as well as maintenance cost variations among segments. Overall, though the rise of EVs means lower maintenance revenues for workshops, profitable segments such as ADAS level 3 and shared car maintenance revenues can offset this. Finally, future researchers are challenged to expand on certain topics covered in this project, especially those for which information available is still scarce.

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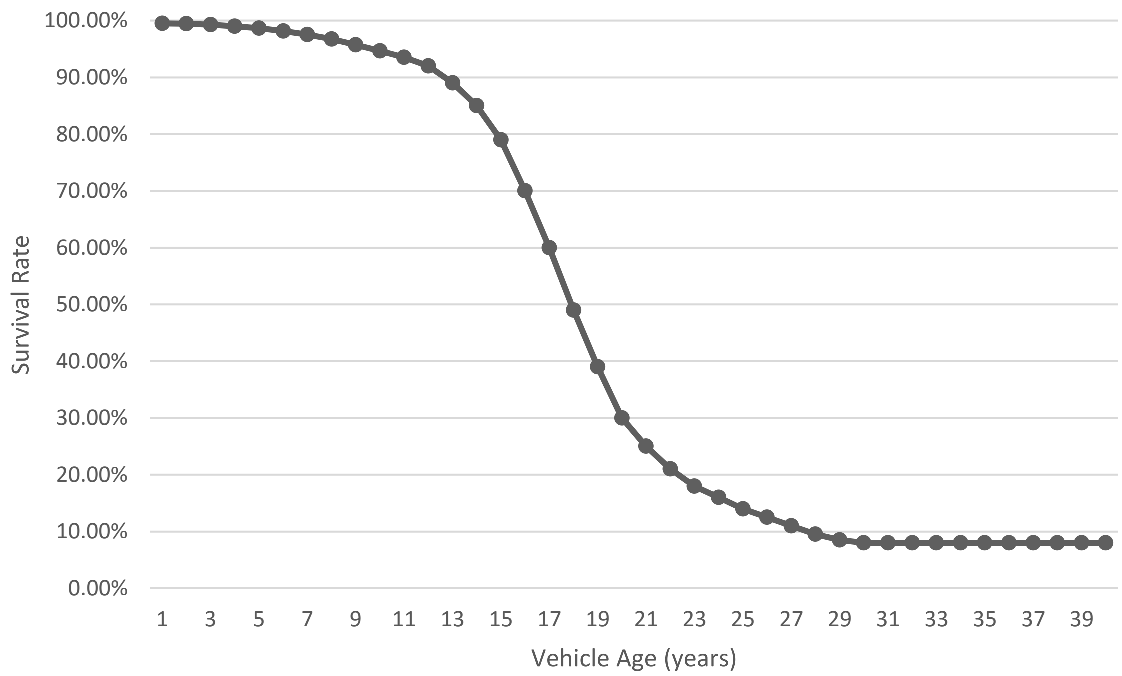
Appendix

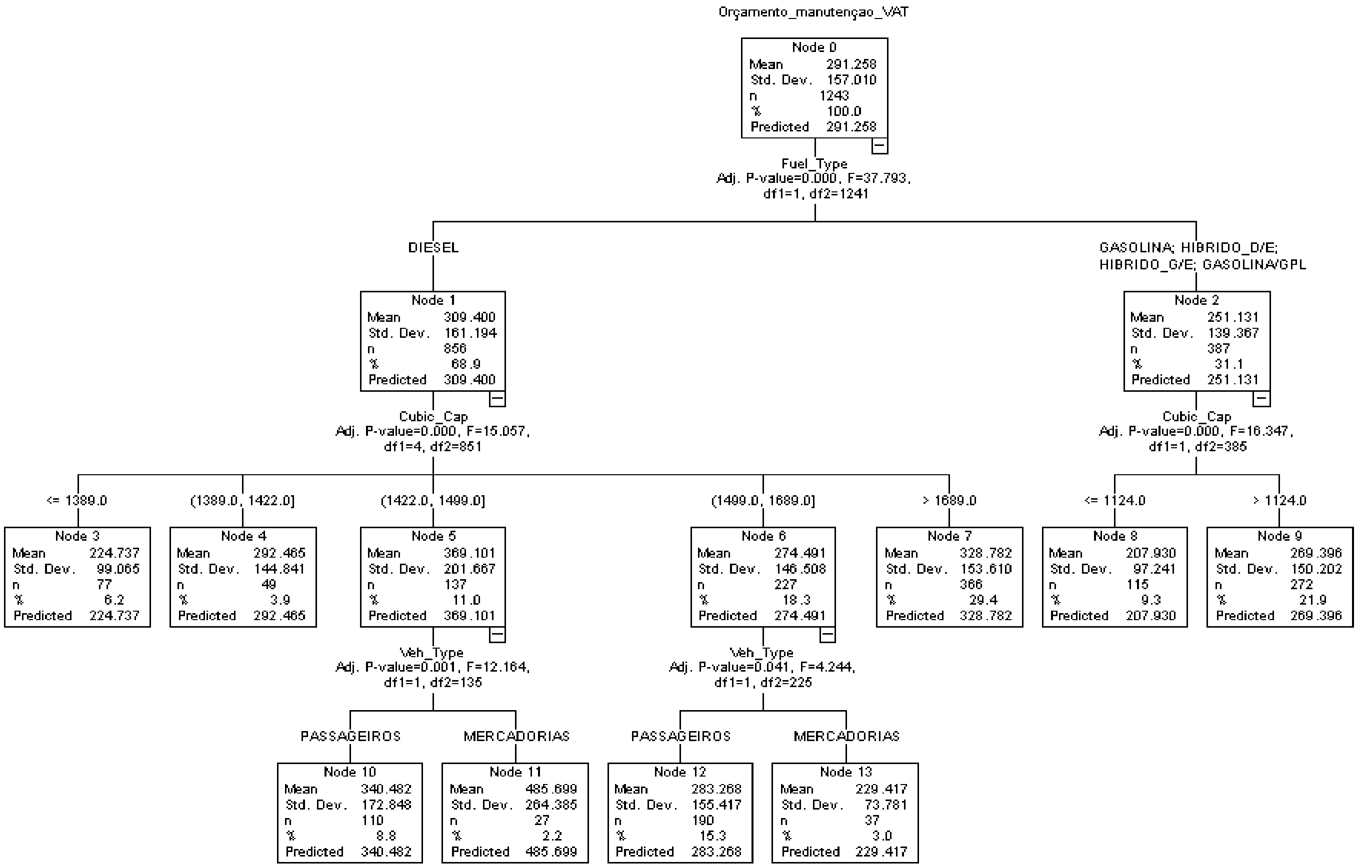
Appendix 1. Average cumulative km per vehicle age

Age (in years)	Average cumulative number of kilometres per vehicles
0	7 471
1	16 727
2	32 274
3	50 116
4	65 914
5	78 669
6	91 690
7	101 010
8	107 089
9	133 434
10	135 145
10 - 15	154 330
15 +	167 194

Appendix 2. Vehicle survival rate per age



Appendix 3. Decision Tree output representing nine vehicle segments



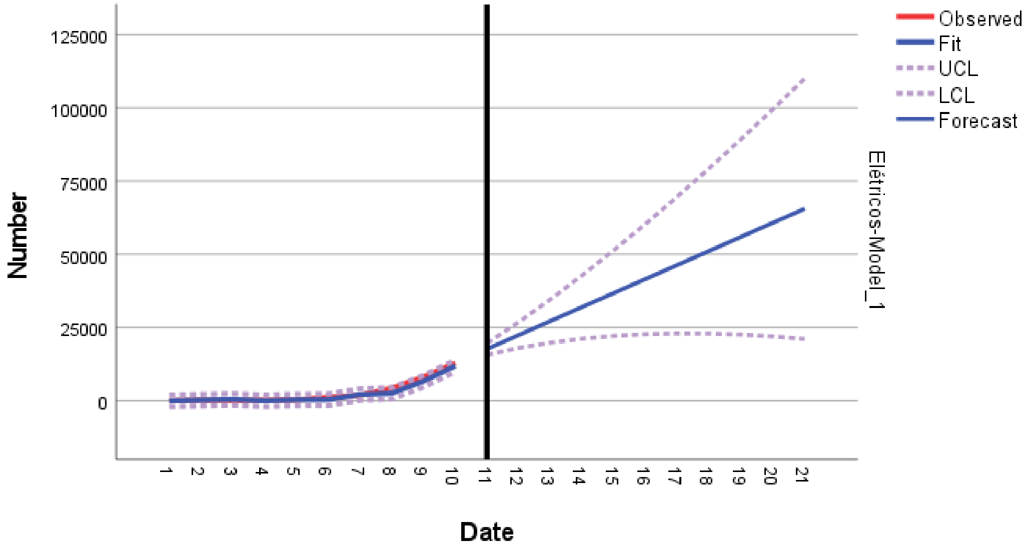
The SPSS CHAID algorithm retrieved nine internal combustion engine segments using the variables Fuel_Type, Cubic_Capacity, and Vehicle_Type as best predictors for maintenance costs. Node 0 represents the entire vehicle sample that is split into smaller nodes until reaching terminal nodes that represent each segment. The mean values of each terminal node correspond to the average maintenance cost of each segment.

Appendix 4. Dickey-Fuller and Phillips-Perron Unit Root tests *p*-values per segment

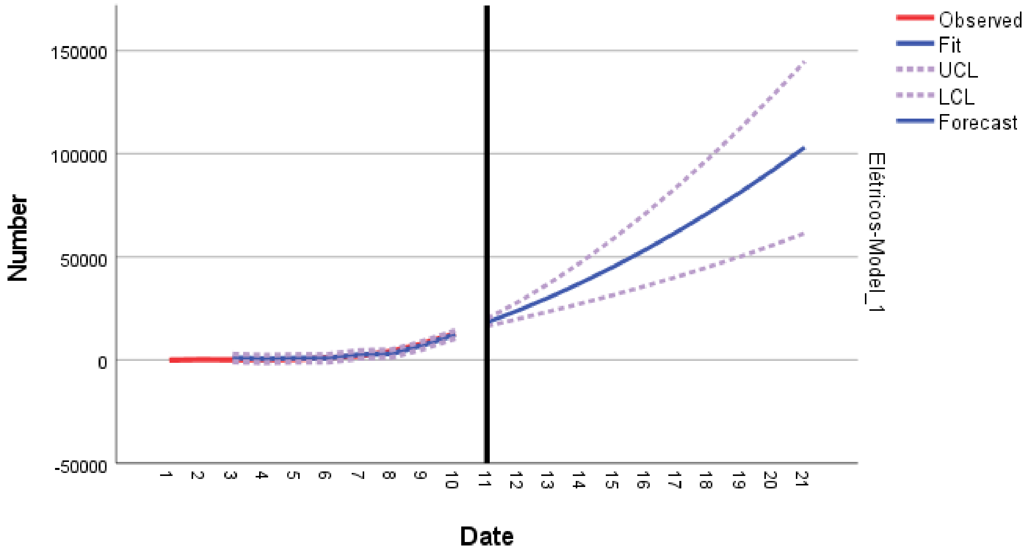
Segments	Dickey-Fuller test	Phillips-Perron Unit Root test
1	0.32	0.79
2	0.86	0.90
3	0.69	0.86
4	0.34	0.66
5	0.31	0.14
6	0.23	0.38
7	0.57	0.87
8	0.42	0.74
9	0.48	0.77
10	0.99	0.99

Appendix 5[20]

Appendix 5.1. The plot of the Holt-Brown's Linear Exponential Smoothing model for annual car entries forecast for the 10th segment (EVs)



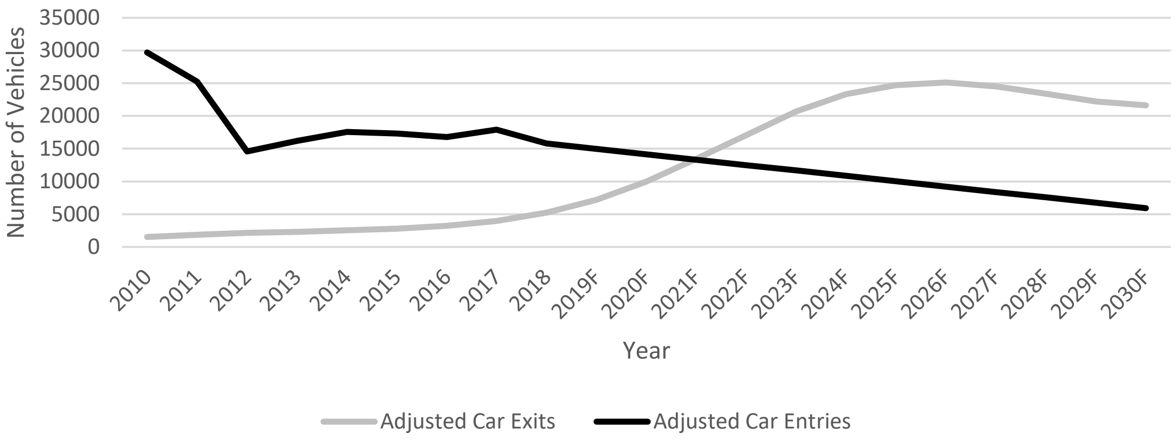
Appendix 5.2. The plot of the ARIMA model for annual car entries forecast for the 10th segment (EVs)



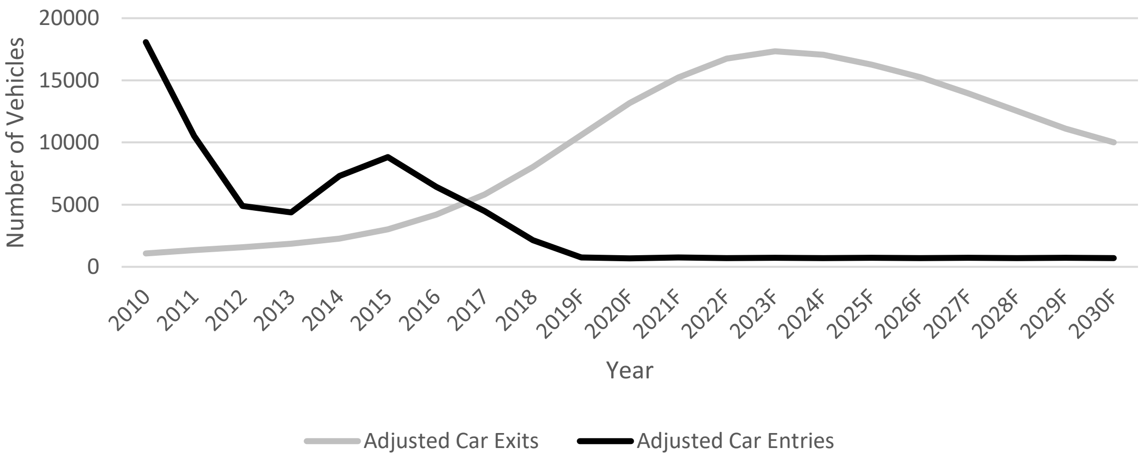
[20] The plots contain both the historical and forecasted car fleet entries, including upper and lower confidence levels. The x-axis represents the period analysed from 2010 to 2030. On the y-axis are illustrated the number of entries in units.

Appendix 6. Adjusted car entries and exits per segment[21]

Appendix 6.1. Adjusted car entries and exits for segment 1

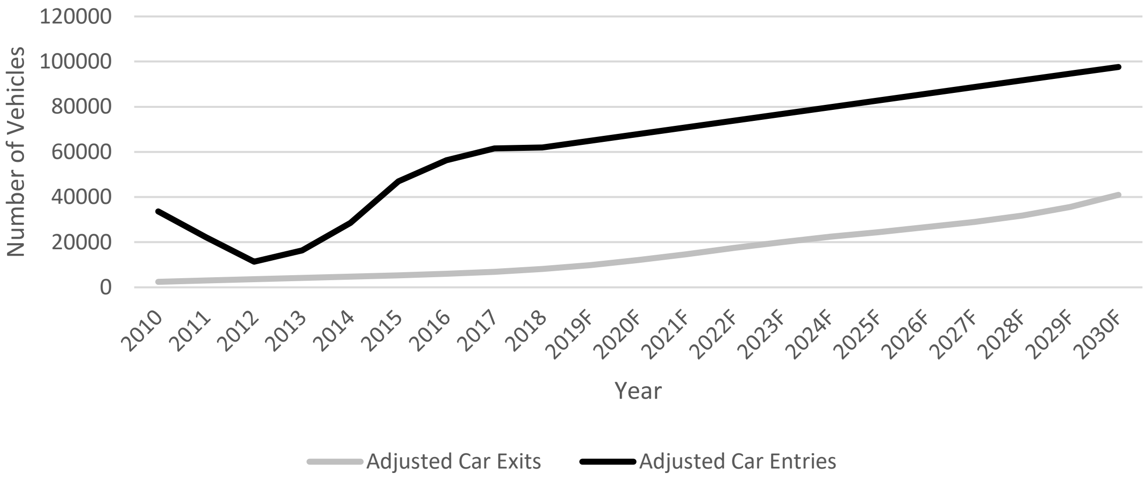


Appendix 6.2. Adjusted car entries and exits for segment 2

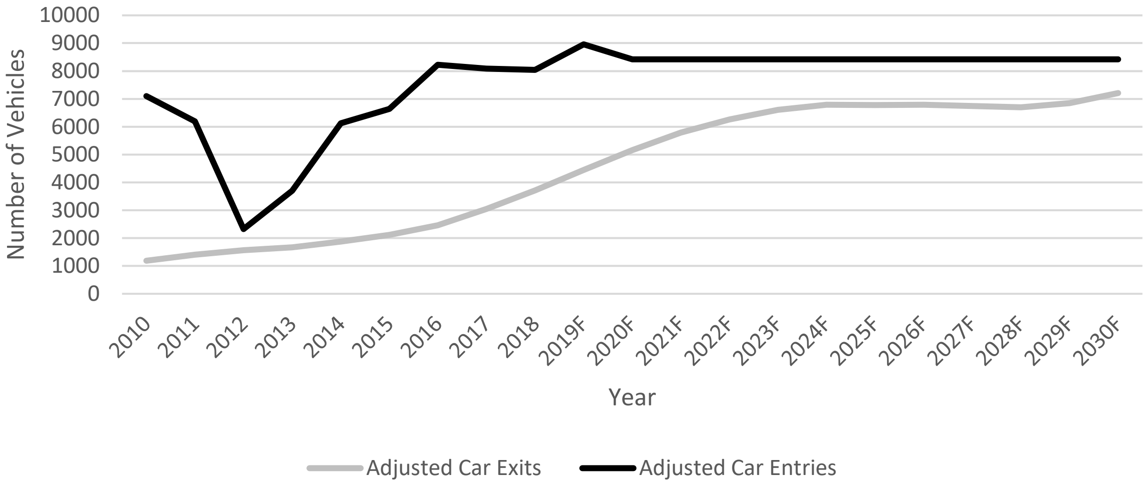


[21] The plots contain the evolution of both the historical and forecasted adjusted car entries and exits over 20 years, using a proportionality factor to solve the overall under-representation issue. Years highlighted with an "F" represent the forecasted period.

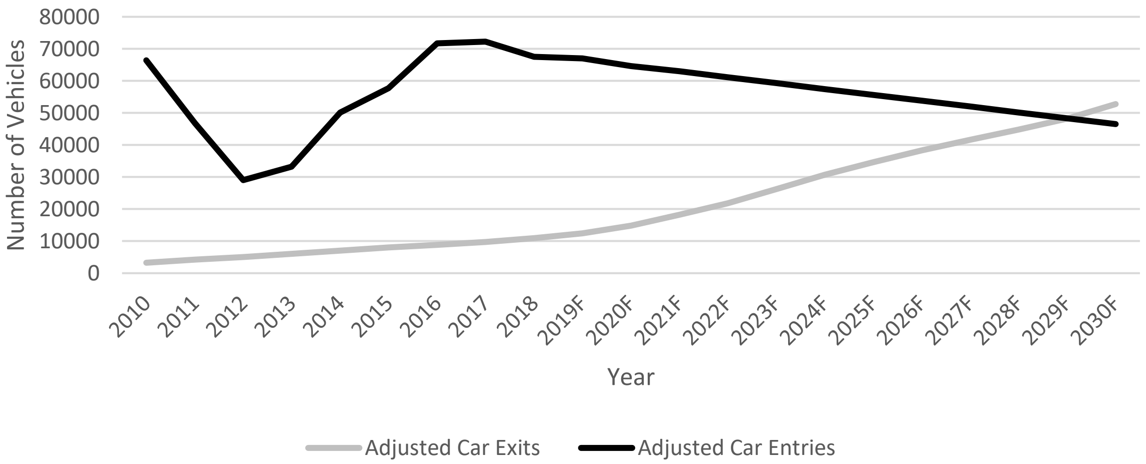
Appendix 6.3. Adjusted car entries and exits for segment 3



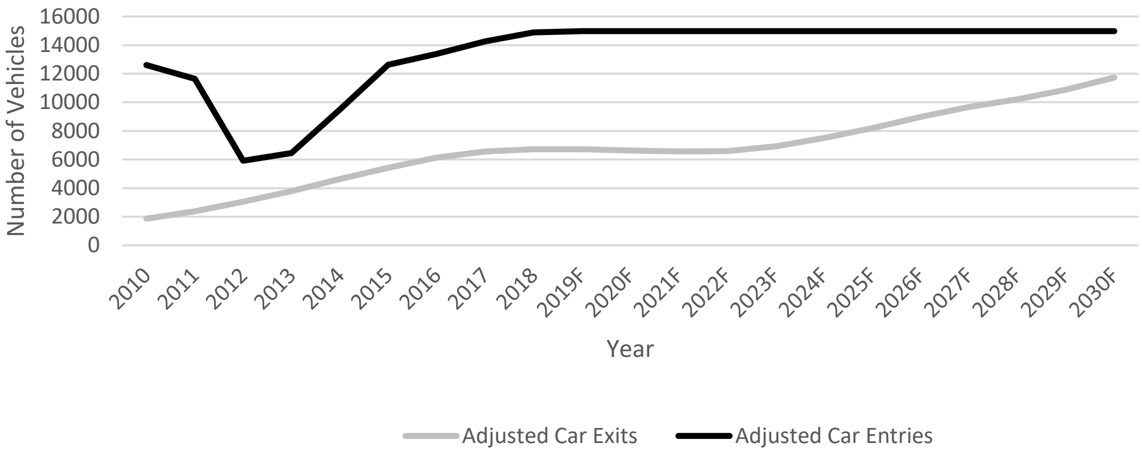
Appendix 6.4. Adjusted car entries and exits for segment 4



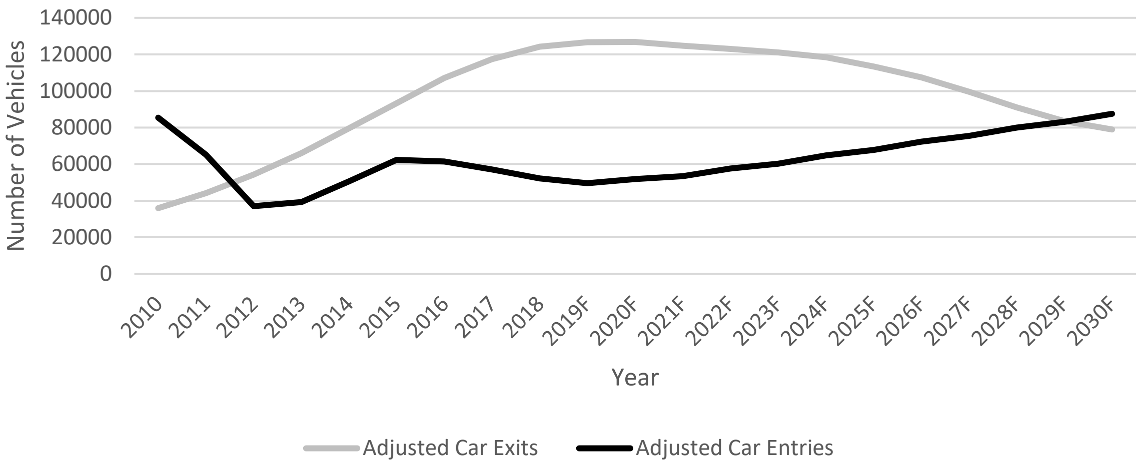
Appendix 6.5. Adjusted car entries and exits for segment 5



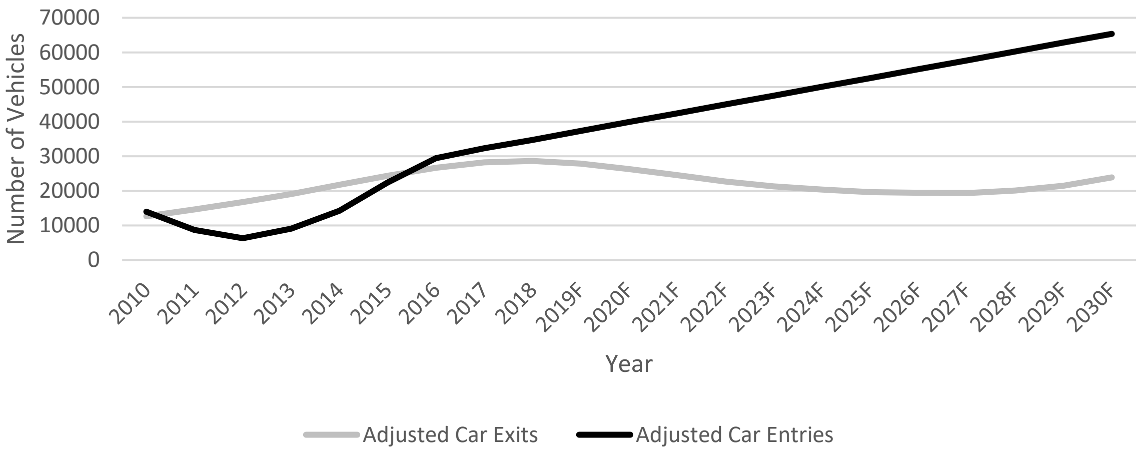
Appendix 6.6. Adjusted car entries and exits for segment 6



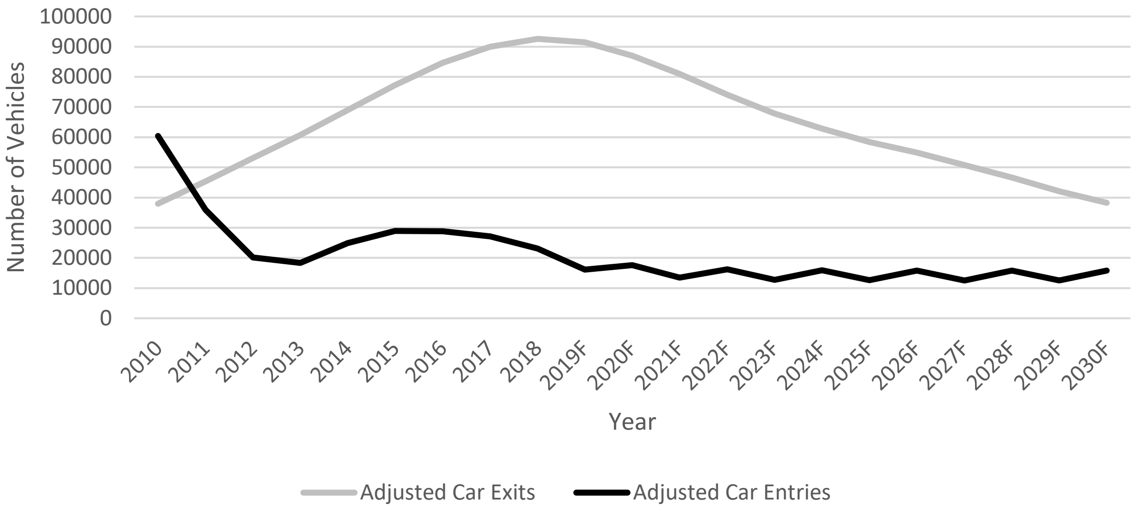
Appendix 6.7. Adjusted car entries and exits for segment 7



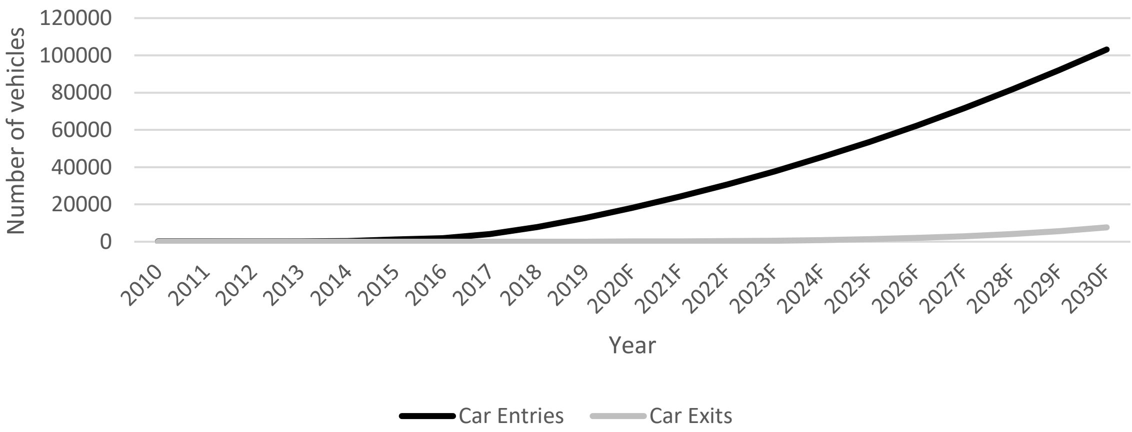
Appendix 6.8. Adjusted car entries and exits for segment 8



Appendix 6.9. Adjusted car entries and exits for segment 9

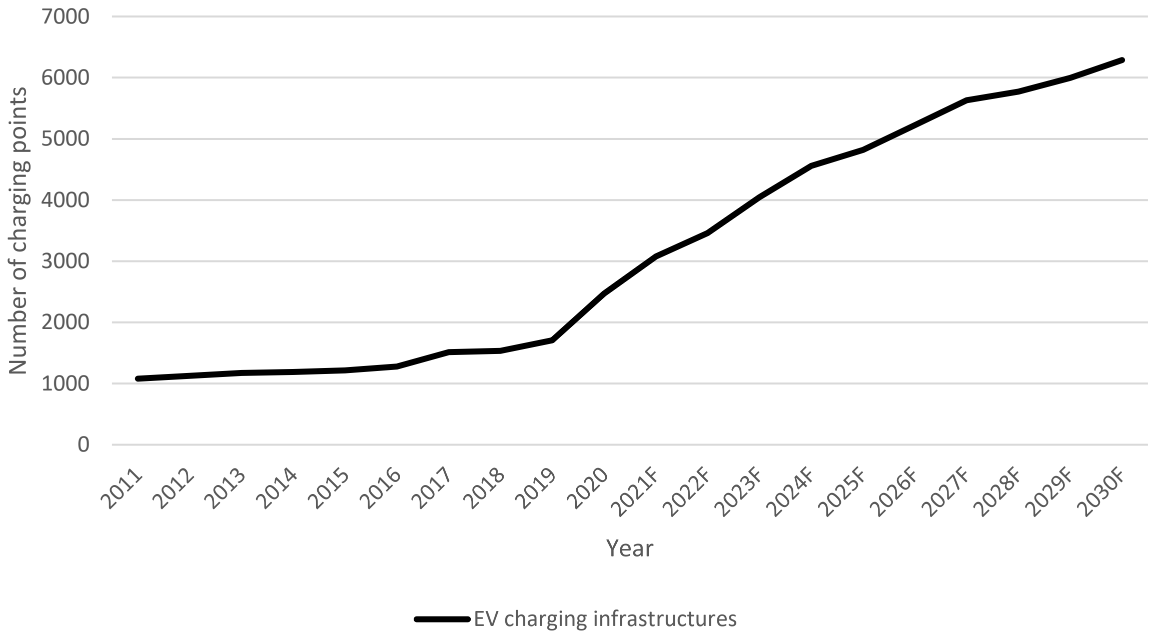


Appendix 6.10. Car entries and exits for segment 10[22]



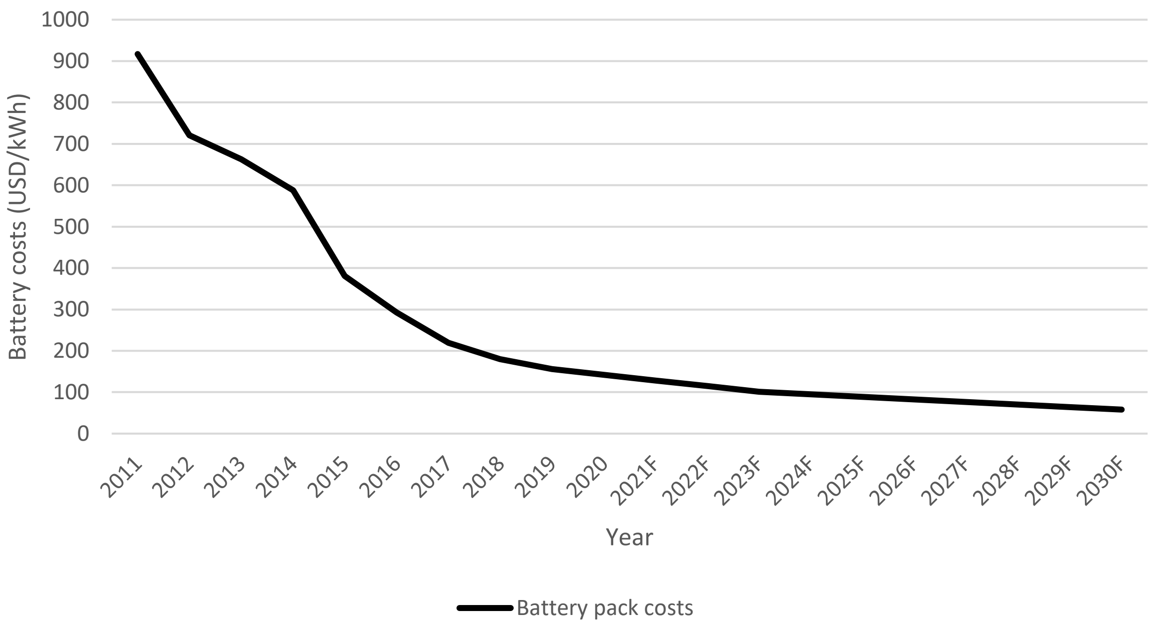
[22] EV entries and exits were not adjusted since entries were retrieved from a dataset containing official aggregated data provided by ACAP. Moreover, this was the only segment where the year 2019 was not forecasted as the official observations were available.

Appendix 7. ARIMA model forecast of EV charging infrastructures in Portugal



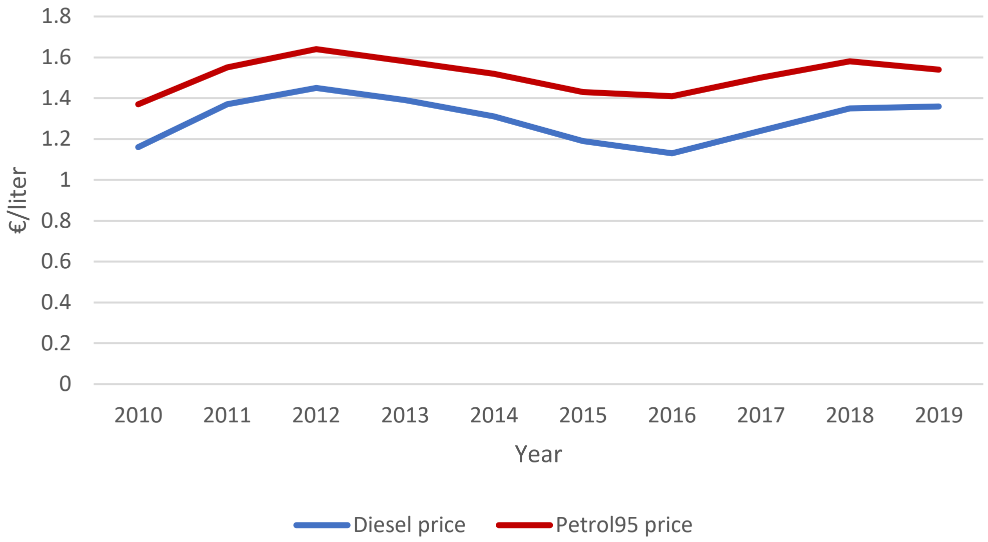
The plot depicts the evolution of both the historical and forecasted number of charging points for EVs in Portugal from 2011 to 2030. Source: European Alternative Fuels Observatory (2020).

Appendix 8. Forecast of EV battery packs average costs



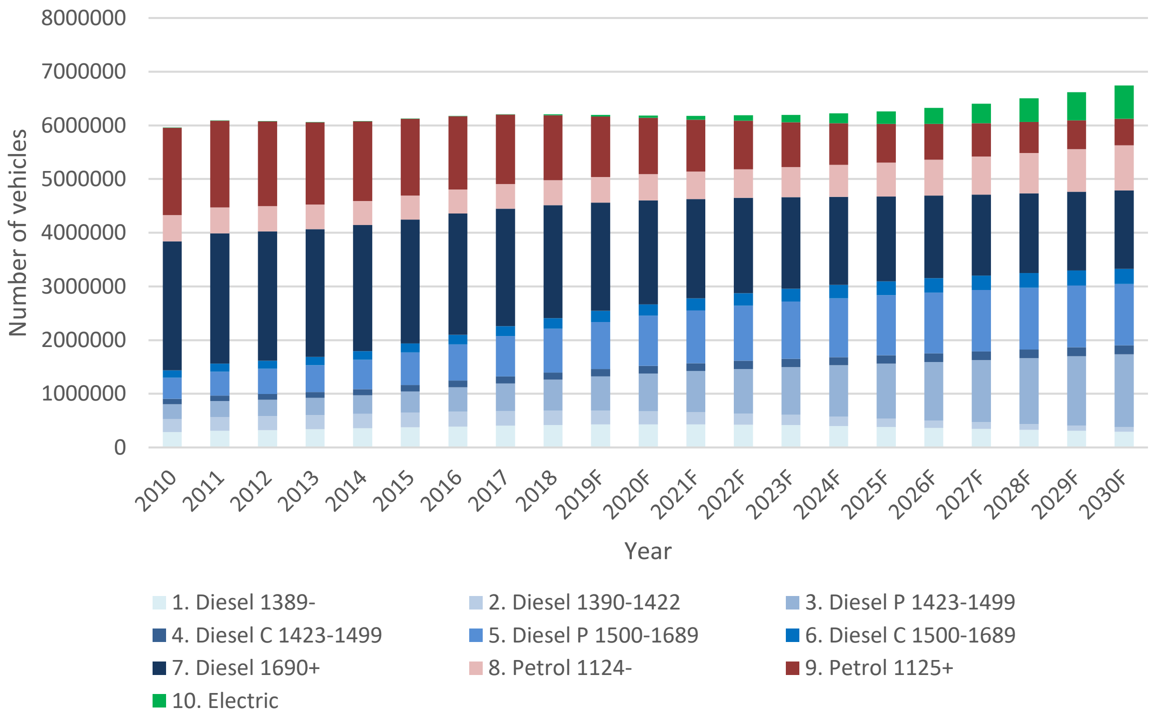
The plot depicts the evolution of both the historical and forecasted EV battery packs average costs from 2011 to 2030. Source: BloombergNEF (2020).

Appendix 9. Diesel and Petrol95 price evolution over a 10-year period in Portugal



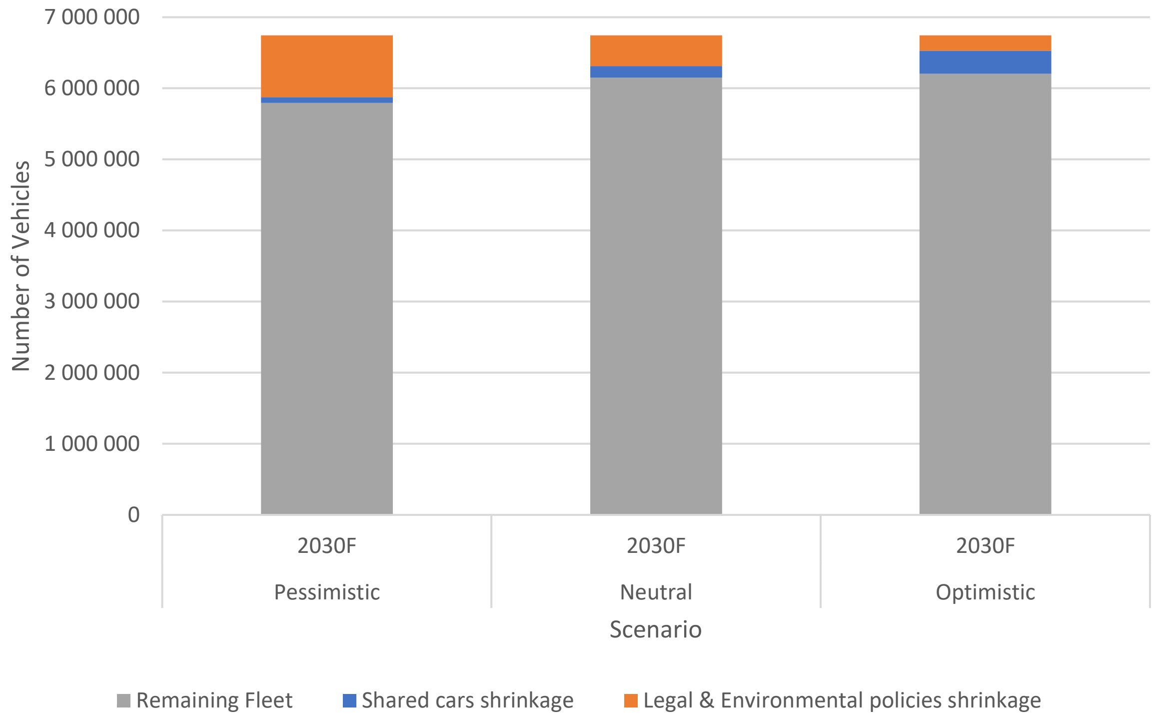
The plot shows the evolution of the historical prices of Diesel and Petrol95 over 10 years in Portugal. Source: PORDATA (2020).

Appendix 10. Evolution of the car fleet per segment over a 20-year period



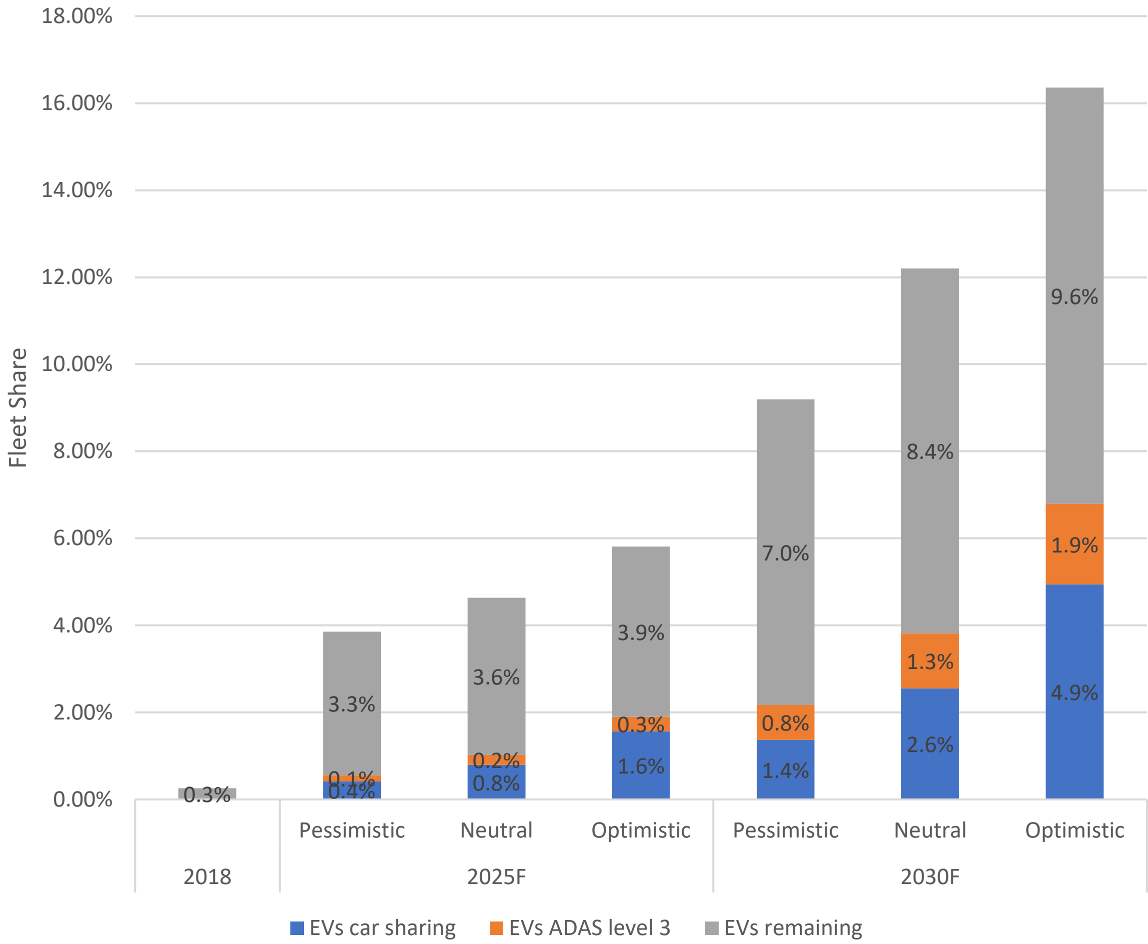
The plot presents the evolution of the Portuguese car fleet composition by segment, without applying the conditioning factors mentioned later in this paper. Results from 2019 to 2030 are forecasted

Appendix 11. The negative impact of legal and environmental policies and the emergence of car sharing in the total car fleet size by 2030



The plot depicts the negative impact of both conditioning factors that contributes to shrinking the number of vehicles circulating over time. Perhaps, the Pessimistic scenario considers a higher impact of legal and environmental policies and a slower diffusion of shared cars. The Optimistic considers the opposite where there is a faster diffusion of shared cars.

Appendix 12. Breakdown of the Portuguese electrified car fleet over a 10-year period



The chart illustrates the expected evolution of the electrified car fleet in terms of car sharing and ADAS level 3 technology. The remaining EVs represent the electrified cars that are expected to be privately owned, without conditioning automation technology.

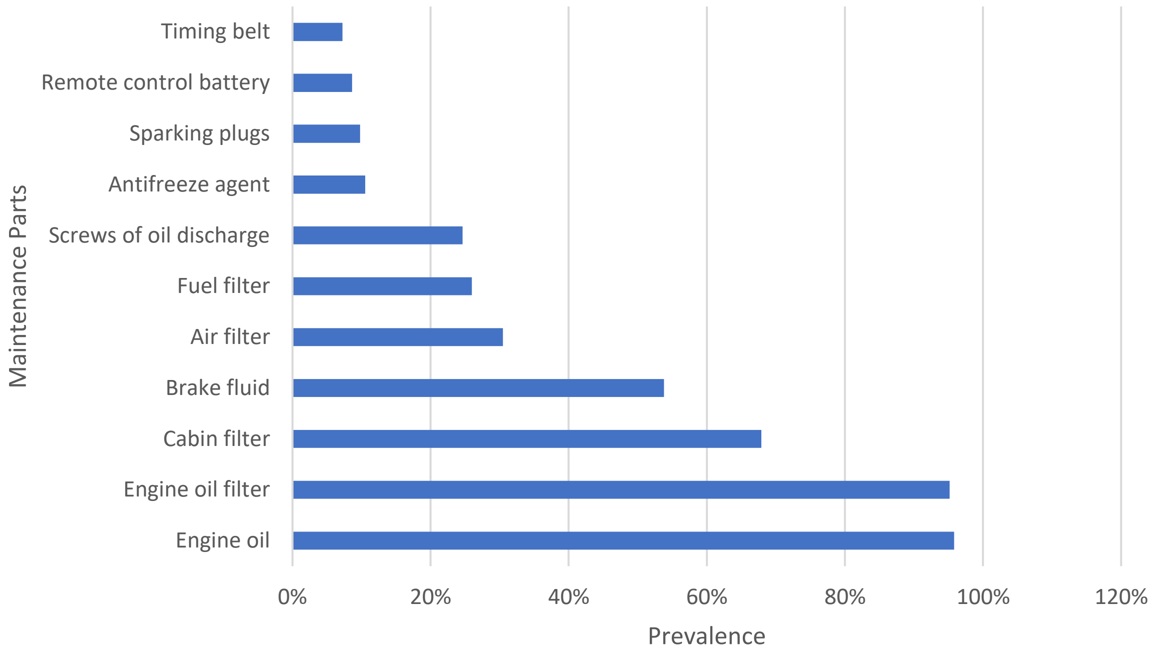
Appendix 13. Vehicle fleet breakdown per type of car fleet and the negative impact of other conditioning factors over time

(in units)	Year	Pessimistic	Neutral	Optimistic
Total fleet without conditioning factors	**2018**	-	6 204 657	-
	2025	-	6 260 232	-
	2030	-	6 744 833	-
Legal and Environmental policies impact	**2025**	-353 116	-176 558	-88 279
	2030	-868 286	-434 143	-217 071
Shared car impact in ICEVs	**2025**	-24 236	-48 472	-96 943
	2030	-80 614	-161 228	-322 457
EVs shared cars	**2025**	24 236	48 472	96 943
	2030	80 614	161 228	322 457
EVs owned cars	**2020**	-	46 715	-
	2025	203 492	233 338	261 915
	2030	459 743	609 022	745 157
ADAS level 3 cars	**2025**	258 165	368 368	478 571
	2030	677 130	861 095	1 045 060
Remaining cars	**2025**	4 429 648	5 447 334	5 354 861
	2030	4 705 774	4 759 001	4 536 341
Car fleet with conditioning factors	**2025**	5 907 116	6 083 674	6 171 953
	2030	5 876 547	6 310 690	6 527 762
Index[23]	**2025**	94.4%	97.2%	98.6%
	2030	87.1%	93.6%	96.8%

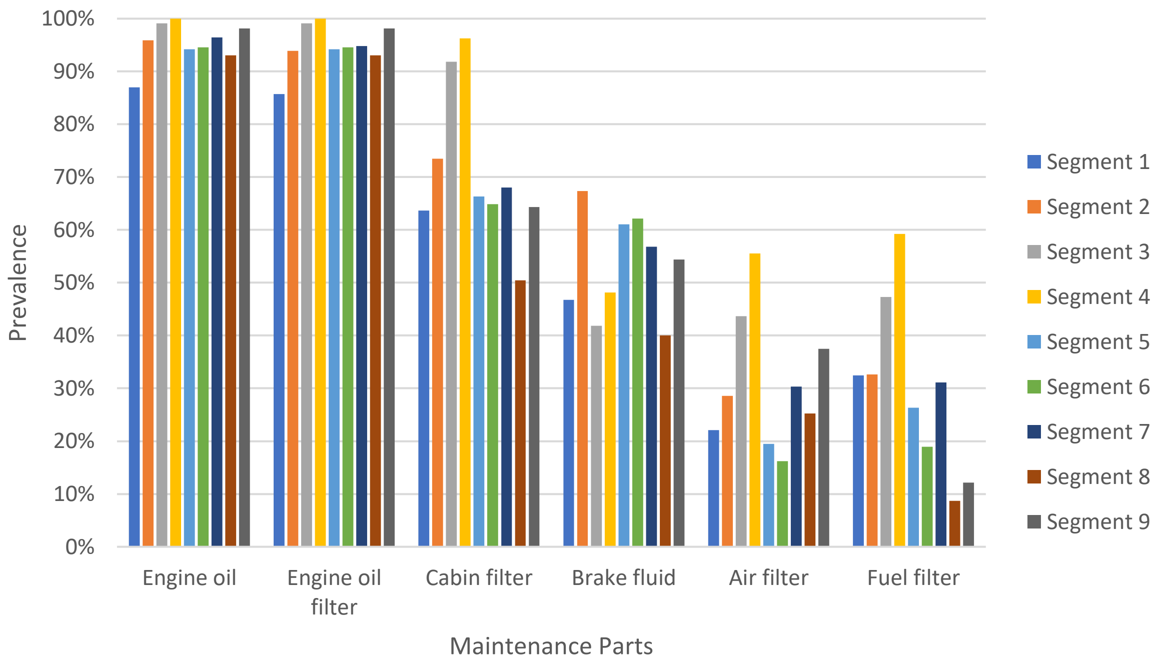
The table contains the forecasted impact of conditioning factors on both future car fleet size and fleet composition. Negative values represent a future shrinkage in the number of vehicles. The remaining conditioning factors with positive values represent the expected car fleet share on the total fleet.

[23] Index = (Total fleet with conditioning factors/ Total fleet without conditioning factors).

Appendix 14. Most frequently replaced maintenance parts

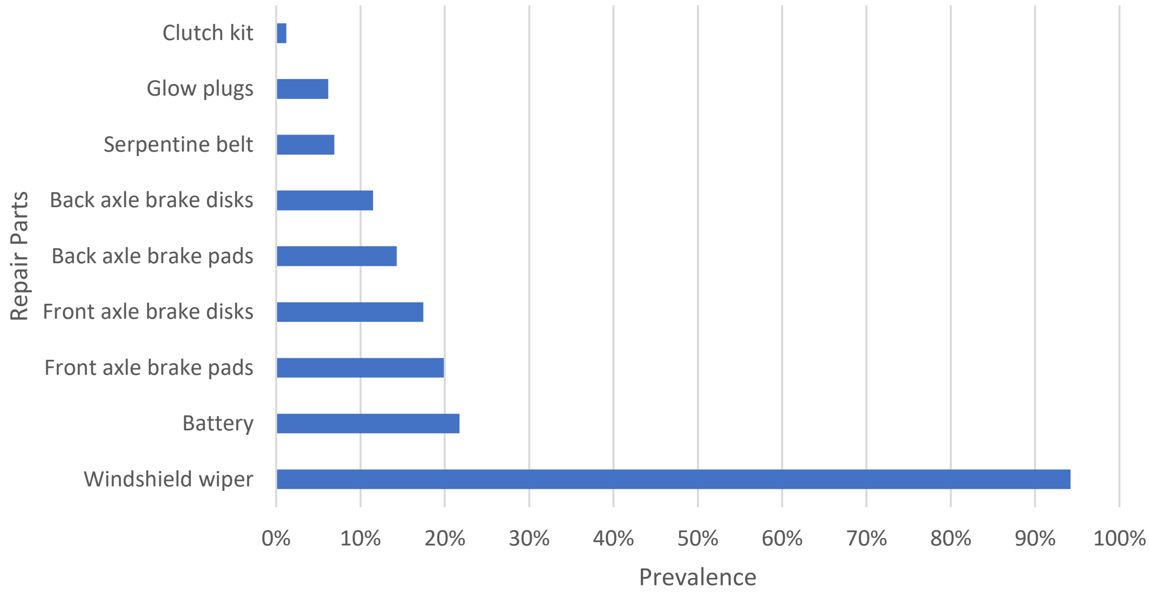


Appendix 15. Most frequently replaced maintenance parts per segment

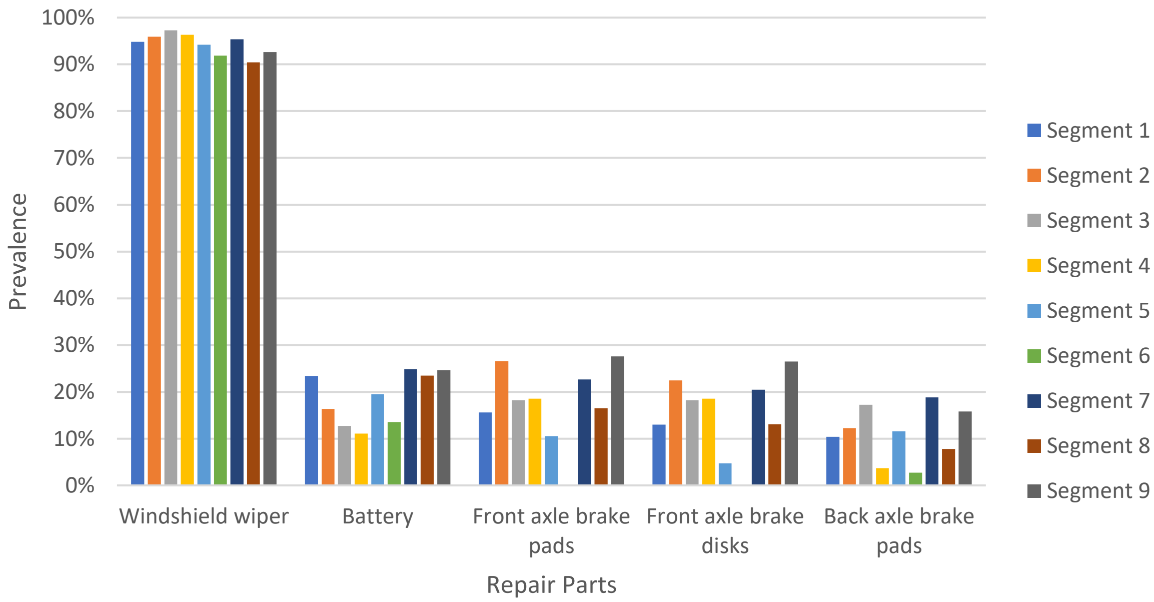


1. Diesel 1389- 2. Diesel 1390-1422 3. Diesel P 1423-1499 4. Diesel C 1423-1499 5. Diesel P 1500-1689
6. Diesel C 1500-1689 7. Diesel 1690+ 8. Petrol 1124- 9. Petrol 1125+ 10. Electric

Appendix 16. Most frequently scheduled repair parts' verifications



Appendix 17. Most frequently scheduled repair parts' verifications per segment



■ 1. Diesel 1389- ■ 2. Diesel 1390-1422 ■ 3. Diesel P 1423-1499 ■ 4. Diesel C 1423-1499 ■ 5. Diesel P 1500-1689
■ 6. Diesel C 1500-1689 ■ 7. Diesel 1690+ ■ 8. Petrol 1124- ■ 9. Petrol 1125+ ■ 10. Electric

Appendix 18. Share of business value per segment without conditioning factors

	2010	2018	2025	2030
Segment 1	3.6%	5.1%	4.7%	3.4%
Segment 2	4.1%	4.3%	2.5%	1.3%
Segment 3	5.3%	10.7%	19.1%	23.9%
Segment 4	2.8%	3.6%	4.1%	4.1%
Segment 5	6.4%	12.6%	17.4%	16.8%
Segment 6	1.8%	2.4%	3.2%	3.3%
Segment 7	45.1%	37.9%	28.5%	24.8%
Segment 8	5.8%	5.3%	7.2%	9.0%
Segment 9	25.1%	17.9%	10.6%	6.9%
Segment 10	0.0%	0.2%	2.6%	6.5%

The table contains the evolution of revenues' share for workshops regarding maintenance operations per segment in four periods of time, without the impact of conditioning factors.

Appendix 19. Average maintenance costs per type of car fleet

(in euros)	Average maintenance cost
ICEVs ADAS level 3	369.7
ICEVs without ADAS level 3	295.8
EVs shared cars	283.7
EVs ADAS level 3	253.3
EVs remaining	202.6

The table depicts the average maintenance costs per type of car fleet. Internal combustion engine vehicles without ADAS level 3 corresponds to the vehicles segmented in the Decision Tree, with a 295.8 euros average maintenance cost. This value was used to calculate the other segments' average maintenance costs by applying percentual decrements or increments.

Appendix 20. Adjusted share of business value per segment with conditioning factors

	2010	2018	2025	2030
Segment 1	3.6%	5.1%	4.7%	3.2%
Segment 2	4.1%	4.3%	2.4%	1.2%
Segment 3	5.3%	10.7%	18.8%	22.8%
Segment 4	2.8%	3.6%	4.1%	3.9%
Segment 5	6.4%	12.6%	17.2%	16.0%
Segment 6	1.8%	2.4%	3.2%	3.2%
Segment 7	45.1%	37.9%	28.1%	23.7%
Segment 8	5.8%	5.3%	7.1%	8.6%
Segment 9	25.1%	17.9%	10.5%	6.6%
Segment 10	0.0%	0.2%	4.0%	10.8%

The table contains the evolution of revenues' share for workshops regarding maintenance operations per segment in four periods of time, with the impact of conditioning factors.

Appendix 21. Business volume breakdown per type of car fleet and the negative impact of other conditioning factors

(in million euros)	Year	Pessimistic	Neutral	Optimistic
Total fleet without conditioning factors	**2018**	-	914.8	-
	2025	913.4	912.0	910.6
	2030	975.3	967.9	960.6
Legal and Environmental policies impact	**2025**	-52.1	-26.0	-13.0
	2030	-128.3	-64.2	-32.1
Shared car impact	**2025**	-3.5	-7.1	-14.1
	2030	-11.7	-23.1	-45.9
ICEVs without ADAS level 3	**2025**	800.4	803.0	789.4
	2030	695.6	703.4	670.5
ICEVs ADAS level 3	**2025**	46.0	65.3	84.4
	2030	116.5	144.4	170.7
EVs shared cars	**2025**	3.4	6.9	13.7
	2030	11.4	22.9	45.7
EVs ADAS level 3	**2025**	1.1	1.8	2.6
	2030	5.9	10.1	15.4
EVs remaining	**2025**	19.8	22.2	24.5
	2030	41.8	53.6	63.2
Car fleet with conditioning factors	**2025**	873.2	904.1	924.5
	2030	879.4	950.7	998.2
Index[24]	**2025**	95.6%	99.1%	101.5%
	2030	90.2%	98.2%	103.9%

The table contains the forecasted impact of conditioning factors on the forecasted maintenance business volume for workshops. Negative values represent future shrinkage in revenues. The remaining conditioning factors with positive values represent the expected share in total revenues.

[24] Index = (Total business volume with conditioning factors/ Total business volume without conditioning factors).