

# Transport energy demand in Andorra. Assessing private car futures through sensitivity and scenario analysis

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## Abstract

This paper builds a model to estimate current car fleet energy consumption in Andorra and forecasts such consumption as a reference scenario. It shows how a useful modelling tool can be developed and applied in the absence of significant data. The base-year model is built through a bottom-up methodology using vehicle registration and technical inspection data. The model forecasts energy consumption up to 2050, taking into account the fleet structure, the car survival profile, trends in activity of the various car categories, and the fuel price and income elasticities that affect car stock and total fleet activity. It provides an initial estimate of private car energy demand in Andorra and charts a baseline scenario that describes a hypothetical future based on historical trends. A local sensitivity analysis is conducted to determine the most sensitive input parameters and study the effect of its variability. In addition, four scenarios are built to represent the largest expected variability in the results with respect to the reference scenario and provide a broad estimate of potential energy savings related to different policy strategies.

## Keywords

Transport; energy demand; Andorra; private car fleet; sensitivity analysis; scenario analysis.

## 1. Introduction

Global energy use in the transportation sector has grown 132% since 1973, a growth that surpasses the overall total energy consumption (92%). Apart from industry, transport is currently the most energy-consuming sector in the world. Although projections to 2035 suggest a more moderate future annual growth (1.4% per annum according to the IEA New Policies Scenario), this figure is far from the stabilization levels required to follow the IEA 450 Scenario, which establishes policies to limit the average global temperature increase to 2 °C (IEA, 2014). Within the European Union framework, the transportation sector accounts for 32% of the final

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energy consumption and is responsible for almost a quarter of the total carbon dioxide (CO<sub>2</sub>) emissions produced, being the sector with the highest growth in both areas since 1990 (European Commission, 2014a). Emissions from the transport sector increased by 33% in the period from 1990 to 2007. However, the recent economic downturn has prevented sustained growth since then. More than two thirds of transport-related GHG emissions are from road transport, contributing approximately 20% of the EU's total CO<sub>2</sub> emissions (European Commission, 2014b). Private cars, as the predominant mode of road transport, have a key contribution to make in decarbonising both European and global economies.

This context points to the need for countries to dedicate greater efforts in defining and implementing effective policies that focus on transport and, more specifically, on minimising energy-related CO<sub>2</sub> emissions. Top-down and, particularly, bottom-up models that quantify the impact of specific governmental policies are widely used to inform and support decision-making processes (Nakata, 2004). In this sense, Bandivadekar and Cheah (2008) evaluate the potential effects of new technologies in the United States using a vehicle fleet bottom-up model. The model examines future vehicle-fuel use based on sales, retirements, fuel consumption and miles driven per year. A similar approach is used by Pasaoglu et al. (2012), implementing a model that analyses the evolution in energy savings, emission reductions and cost aspects of future vehicle options in the EU-27 under various vehicle penetration scenarios. Daly and Ó Gallachóir (2012) use a technological model of Ireland's future car stock to simulate the impact of a range of policy strategies that focus on vehicle efficiency, fuel switching and behavioural measures. Local policies such as fiscal measures (i.e. vehicle and fuel taxation) are evaluated in national-scale models such as that used in the UK Transport Carbon Model (Brand et al., 2012) or in Kloess and Müller (2011) where the Austrian passenger car fleet is simulated. *Ex-post* analysis of car taxation policies has also emerged with case studies being completed in Ireland (Rogan et al., 2011) and in France (D'Haultfœuille et al., 2014).

Most of the studies developed in this field are concentrated in countries where the availability of data is very high and where there is previous research that can support the construction of new models. In countries where less data is available, simplifications and estimates are required in order to build these models. This paper focuses on this challenge in energy modelling research. The variability in the model outputs, associated with uncertainties in input parameters, may be even greater in these cases. In this sense, greater emphasis on analysing possible output variability is needed to give policymakers greater confidence in the forecasts derived from such models.

This paper builds a private energy model for the car stock in Andorra. Its purpose is to demonstrate how a useful modelling tool can be developed and applied in the absence of significant data. The approach adopted here has the potential to be replicated in other regions that require further evidence to underpin policy decisions, but where data scarcity exists.

The model estimates current and future car transport energy demand in Andorra. It is currently limited to a reference scenario, however the paper shows the subsequent steps that are required to enable additional scenario analysis, so that the model can be used to support national policy decision-making processes by quantifying the impacts of various energy policy measures.

Andorra is a small, mountainous country located between France and Spain, with a population of approximately 70,000 inhabitants in 2014 and an area of 468 km<sup>2</sup>. Andorra is highly energy import-dependent. Only 4% of the energy used in the country derives from locally generated electricity. The remaining 96%, including all hydrocarbon fuels used in transport sector, is imported from France and Spain. Despite this high dependency on energy imports, electricity

and hydrocarbon fuels are cheaper than in neighbouring countries due to Andorra's fiscal policy. The ratio of private cars per population is among the highest in the world (686 cars per 1,000 inhabitants). Despite the decline in car sales since 2005, the total car stock has continued to rise, undeterred by the economic downturn (Department of Statistics, 2014). This case study is particularly relevant, as in Andorra, the transport sector is the main energy consumer (50% of the final energy consumed in 2013) and the leading source of GHG emissions, representing 69% of energy-related emissions (Miquel et al., 2014). Its location, in the middle of the Pyrenees, means that transport energy demand is entirely focused on road transport. Moreover, nearly 8 million people visit Andorra by road every year, representing an important contributor to national fuel consumption. Although there is no previous research addressing this aspect, according to the vehicle fleet structure, private cars (72% of the fleet) seem to have a major impact on transport energy demand. Thus, it is particularly critical to quantify the importance of private car energy demand, improve understanding of the country's drivers and show possible future trends in order to deal with energy challenges in the coming years.

The private car energy model implemented in this paper follows essentially that proposed by Daly and Ó Gallachóir (2011a), but it has been modified and adapted to account for data scarcity, such as that found in the case of Andorra. It can be classified as a bottom-up simulation forecasting model, where energy demand is driven by the technological composition of the car stock and the behaviour of private car users. A demographic model of the car stock has been created and the technological characteristics (fuel type, engine size and car age) have been disaggregated by year.

The paper is organised as follows. The methodology and assumptions are presented in Section 2. Section 3 provides the results and discussion. Finally, conclusions, policy implications and some prospects for future work are presented in Section 4.

## **2. Methods**

The model presented in this paper has been developed in two main steps. Firstly, a technological stock model of private car energy demand has been built. Andorra's current private car fleet has been modelled, including highly detailed vehicle technological characteristics, to provide energy demand results for the year 2013. Then, the stock model has been projected for each year up to 2050, based on historical trends and guided by economic factors and technological innovation. Finally, the effect of the variability in input parameters has been studied through a sensitivity analysis and different scenarios have been analysed in order to quantify the potential of technology- and behaviour-focused policies.

### *2.1 Car fleet model*

This model represents Andorra's current car fleet. It is a technological car stock model built through a bottom-up methodology using the country's vehicle registration data (Daly and Ó Gallachóir, 2011b). It uses fleet structure, mileage profile (km/year) and specific energy consumption (MJ/km) as explanatory variables (Fig. 1). The private car fleet in 2013 is disaggregated into different categories according to fuel type, engine size and vintage (car age). Subsequently, a mileage profile for different car categories has been defined, based on data from vehicle technical inspections. Each category has a specific energy consumption value, which takes into account official fuel consumption test data, on-road factor (to reflect the gap between real and test vehicle efficiency), and ageing factor (to include vehicle vintage in car consumption).

### 2.1.1 Car fleet structure

Andorra's 2013 private car fleet is built using data compiled from the National Vehicle Registration bureau up to the end of 2013 (Department of Industry, 2014). Although the database contains technological details from all vehicles registered since 1951 still remaining in the car fleet, it does not include any information on the fleet structure for years before 2013 or historical scrapped vehicles. Fig. 2 shows Andorra's 2013 private car fleet. All cars registered after 1984 (49,691 individual records) have been filtered and disaggregated into different categories according to fuel type (petrol or diesel), engine size (<1400 cc, 1400–2000 cc, >2000 cc) and vintage (0–29 years), factors that have a major influence on energy consumption.

The entire fleet is distributed into diesel and petrol cars, since other technologies are not relevant in the current car fleet. Electric vehicles are not considered in the model due to their low penetration in Andorra (1 registered car at the end of 2013). Likewise, hybrid electric vehicles are counted but not treated as a different category, because they only represent 0.26% of the car fleet (Department of Industry, 2014). The type of fuel used has an important influence on the vehicle's specific energy consumption and the mileage profile. In general, diesel cars are more fuel-efficient than petrol cars. However, the engine capacity and driving distances of diesel cars are generally greater, resulting in no significant improvement in the final energy consumption in some cases (Schipper, 2008; Sprei and Karlsson, 2013).

There is a positive relationship between car engine size and fuel consumption. Kwon (2006) provides a regression model of the fuel consumption rate and the engine capacity for 2001 new registered cars in Great Britain. According to his model, the fuel consumption rate of petrol cars increases by 0.58% when the engine capacity of the car increases by 1%.

Age is also a determining factor in fleet energy consumption due to improved new car efficiency over time, increased fuel consumption and generalized mileage decrease over car lifespan (Zachariadis et al., 2001). In this model, car vintage is derived from the year of manufacture and the fleet is vintaged up to 29 years.

The current structure of the fleet reflects sales trends and retirements over the last thirty years. The effects of economic prosperity (i.e. when car sales were high) can be observed in years running up to and after 2005, followed by an economic recession where a drop in new registered vehicles can be observed. The persistent shift to diesel cars, which represents 65% of cars in the current fleet, can also be seen.

### 2.1.2 Annual mileage profile

Road traffic statistics in many countries report that vehicles tend to be driven less as they get older (Zachariadis et al., 2001). Technological parameters, such as fuel type and engine size, not only affect the final energy consumption through specific fuel consumption, but also through mileage. Therefore, average mileage per car type trends (Daly and Ó Gallachóir, 2011b) need to be analysed. The average vehicle kilometres per year for each category is estimated in the model using 2013 data from vehicle technical inspections in Andorra (Department of Industry, 2014). The data is limited to cars that have completed the inspection that year (around 20% of the fleet). The mileage profile for each fuel type and engine size follows a negative exponential function of the form

$$M = M_0 \cdot e^{-\beta \cdot a} \quad (1)$$

where  $M$  is the average mileage for a determined car age,  $M_0$  is the average mileage for new registered cars,  $\beta$  is the mileage decay factor, and  $a$  is the car age. Fig. 3 shows the mileage profiles obtained in 2013. As it can be observed, diesel cars tend to drive longer distances than petrol ones with a similar mileage decay over time. This trend is comparable to others obtained in similar studies for other countries (Hickman et al., 1999) and with different methodologies (Daly and Ó Gallachóir, 2011b). With regard to engine capacity, larger-sized engine cars tend to drive more kilometres per year than other categories in the first years of life. On the other hand, for both fuel types, the mileage decay during its lifetime is greater than for medium and small-sized cars.

### 2.1.3 Specific energy consumption

Specific fuel consumption (SFC) data is not included in the Andorra's vehicle registration data. Here the UK's Vehicle Certification Agency (VCA) database<sup>1</sup> has been used instead, in order to overcome this difficulty. This web-enabled tool provides data on the fuel consumption of most of the new and used cars in the UK, expressed in litres of fuel per 100 km. These units are then converted to MJ/km and combined with the 2013 car stock data to produce figures of average specific energy consumption (SEC) of new cars for each fuel type, engine capacity and vintage (Fig. 4). The VCA data is based on the New European Driving Cycle (NEDC), the legislative cycle in the EU countries for certifying vehicle fuel consumption and emission levels. As fuel economy test procedures are mandatory in Europe for new cars since 1 January 2000, previous SEC values have been extrapolated following 2000–2013 trends.

There is a gap between the NEDC SEC values and the actual performance levels obtained under real-world conditions (Smith, 2010; Tzirakis et al., 2006), due to the fact that they do not take into account parameters such as frontal area or drag coefficient of the car, which clearly affect fuel consumption (Burgess and Choi, 2003). Increased congestion, intense driving style and the penetration of additional electric devices are other factors that aggravate real-world energy consumption (Papagiannaki and Diakoulaki, 2009). In addition, in the particular case of Andorra, the high grades of its roads have a major impact on energy consumption. In analysing the gap between fuel economy under the NEDC and under real driving conditions in Andorra, a gap of 39.6% between NEDC consumption and real-road figures (Travesset-Baro et al., 2015) has been shown. In this paper, this value is assumed as an on-road factor, which is applied to all car categories. While the on-road factor estimates are generally lower (around 20%) in other countries (Daly and Ó Gallachóir, 2011b; Fontaras and Dilara, 2012; Zachariadis, 2006), the difference here comes from the high road grades in Andorra and the increase in the on-road factor over the last decades. According to Zachariadis (2006), it is very likely that the on-road factor will increase further in the future, considering the particularities of the European car market. This trend is confirmed in the recent report published by the International Council on Clean Transportation (Mock et al., 2014).

A decreasing fuel economy is observed in vehicles over their lifetime. According to the assumptions considered in Daly and Ó Gallachóir (2011b), in order to reflect this factor, the vehicle's SEC is increased by an ageing factor of 0.3% for each year in its lifetime.

### 2.1.4 Car fleet real-road energy consumption

Combining all factors explained above, the fleet's annual final energy consumption is calculated according to the equation:

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<sup>1</sup> <http://carfueldata.direct.gov.uk/>

$$FE = \sum_{f,cc,a} S_{f,cc,a} \cdot M_{f,cc,a} \cdot SEC_{f,cc,a} \cdot ORF \cdot A_a \quad (2)$$

where  $FE$  is the car fleet's annual final energy consumption,  $f$  is the fuel type,  $cc$  is the engine size,  $a$  is the car age,  $S$  the car stock,  $M$  the mileage,  $SEC$  the specific energy consumption,  $ORF$  the on-road factor, and  $A$  the ageing factor.

## 2.2 Model forecast

A spread sheet-based model that tracks stock, mileage and specific energy consumption for each year has been built to forecast private car fleet energy demand in Andorra. The "ODD" (Overview, Design concepts and Details) protocol (Grimm et al., 2010, 2006), an accepted standard for describing models in ecological and social sciences, is used here to formulate and describe the model. Although this protocol was originally intended to standardise written descriptions of agent-based models (ABMs), it is considered useful to make the model more understandable and reproducible.

### 2.2.1 Purpose

The purpose of the model is to analyse the future private car fleet energy demand in Andorra. It is designed to create a realistic baseline scenario to be used as a reference in exploring the potential of different policy measures.

### 2.2.2 Entities, state variables and scales

The entities of the model are private cars from Andorra's car fleet. Cars are classified into differentiated categories according to fuel type, engine size, and car age (vintage), maintaining the structure described in the base-year model (Section 2.1.1). Each category is characterised by its stock (number of cars), mileage (km/year) and SEC (MJ/km), which are updated every time-step, driven by expected economic and technological trends. One time-step of the model corresponds to 1 year and the simulation is run for 37 years (from 2013 to 2050).

### 2.2.3 Process overview and scheduling

The simulation starts with the car fleet's structure at the end of the base year (i.e. 2013). Using the survival rate profile for private cars in Andorra, the model calculates car retirements for the next year. The overall fleet size is projected for each year as a function of oil prices and the country's gross domestic product (GDP) growth. Elasticities of vehicle stock with respect to fuel price and income are used to describe this trend. Once the retirements and the number of cars in the stock are determined, new registered cars are calculated as:

$$\text{New registered cars } (t) = \text{Stock } (t) - \text{Stock } (t - 1) + \text{Retirements } (t) \quad (3)$$

New cars are then entered into the fleet with a car category share driven by GDP growth and observed historical trends. At the same time, mileage for each car category is calculated, taking into account the base-year mileage profile (as described in Section 2.1.2) and the evolution of total car fleet activity in vehicle kilometres (vkm). It is projected using elasticities in a similar way as with the overall car stock, with oil prices and GDP growth as main drivers.

The SEC of new petrol and diesel cars is assumed to improve by 1.3% from 2013 to 2020, and for the period 2020–2050, modest annual energy efficiency improvements of 0.5% are assumed (Pasaoglu et al., 2012). As explained in Section 2.1.3, the new car SEC is adjusted by car vintage, applying an ageing factor of 0.3% per year. Furthermore, to characterise the gap between NEDC

consumption and real-road figures, a constant on-road factor of 39.6% is applied to all cars of the fleet.

The last stage for each time-step (year) is to calculate the car fleet's final energy consumption using Eq. (2). The flowchart in Fig. 5 shows an overview of the model.

#### 2.2.4 Design concepts

The model presented in this paper has a general bottom-up structure, where energy demand is driven by the technological composition of the car stock and the behaviour of private car users. The high level of detail provided by the bottom-up modelling approach allows the model to explore the potential of specific policy measures. In order to develop the forecast, the technological model is combined with a top-down econometric model to characterise the future evolution of Andorra's car transport demand, overall stock and the characteristics of new registered cars according to macroeconomic trends.

#### 2.2.5 Initialisation

The model starts the simulation with data from the base-year model, as described in Section 2.1. Initially, there are 49,691 cars in the overall car fleet with a predominant weight of diesel and medium-sized engine (1400–2000 cc) vehicles. The average mileage per car is 10,849 km/year and the total car fleet activity is 539.12 million vkm.

#### 2.2.6 Input data

Some external sources are used as input data to implement the model. Standard elasticity values for vehicle stock and car fleet activity with respect to fuel price and income are taken from Goodwin et al. (2004) and shown in Table 1. Here, elasticity is defined as the percentage change in stock and activity demand that would result from a one percentage change in oil price or the country's GDP, taken as proxies of fuel price and income, respectively.

To establish the category share of new registered cars, the model uses engine-size elasticities based on the values defined in Daly and Ó Gallachóir (2011a). The assumed values are shown in Table 2. The economic factors are related to oil prices and GDP forecasts. The former are based on the prices considered in the reference scenario from the *Energy Roadmap 2050* (European Commission, 2011). Andorra's future real GDP is based on economic projections from *First biennial report of Andorra to the United Nations Framework Convention on Climate Change* (Miquel et al., 2014).

#### 2.2.7 Submodels

##### *Stock*

The overall fleet size is projected with a top-down econometric model. While an increase in GDP causes a rise in car stock, rising oil prices negatively affect the fleet size. Income elasticity of demand (IED), price elasticity of demand (PED), GDP growth ( $\Delta GDP$ ), and oil price growth ( $\Delta OP$ ) are used to capture this behaviour at an aggregated level:

$$Stock(t) = Stock(t - 1) \cdot (1 + \Delta GDP(t) \cdot IED) \cdot (1 + \Delta OP(t) \cdot PED) \quad (4)$$

Retirements and new registered cars are used to reflect the share of different car categories over time. Retirements are calculated for each category, year by year, according to car age and survival rate profile using the equation:

$$Retirements(t)_{f,cc,a} = Stock(t-1)_{f,cc,a} \cdot (1 - Survival Rate_a) \quad (5)$$

*Survival Rate* describes the probability that a car with age  $a$  survives in year  $t$ . There is a considerable uncertainty about the car's survival rate due to a number of factors, including the reliability of new vehicle technology, economic factors that could result in consumers keeping their cars for a longer or shorter period of time, technology developments that could result in vehicles becoming more durable and reliable, as well as greater safety provisions as a result of new regulations and scrappage policies (Bastani et al., 2012). In Andorra, there is no consistent data on the life expectancy of different car categories, since disaggregated historical retirements figures are not available. In absence of more detailed information, aggregated new registered cars (from year  $y$  1993 to 2013) and current stock vintage are used to calculate survival rate according to car age, using the equation:

$$Survival Rate_a = Stock_a / New\ registered_{(t-y)} \quad (6)$$

As historical data is only available for the last 20 years and the stock is vintaged up to 29 years, it is necessary to model a survival rate profile. Two general approaches can be used to determine fleet survival rate. These methods include using the logistic curve (Bandivadekar and Cheah, 2008; Bastani et al., 2012; Feeney and Cardebring, 1988; Greene and Chen, 1981) or the Weibull distribution function (Kloess and Müller, 2011; Kwon, 2006; Zachariadis et al., 2001). For the purpose of this model, the survival rate of new vehicles is determined by using a logistic curve as shown in Eq. (7).

$$Survival Rate(t) = 1 - \frac{1}{\alpha + e^{-\beta \cdot (t-t_0)}} \quad (7)$$

where  $t_0$  is the median lifetime of the stock,  $t$  the age on a given year,  $\beta$  a growth parameter translating how fast vehicles are retired around  $t_0$ , and  $\alpha$  a model parameter.

Calculated survival rate data from 1993 to 2013 is fitted to the logistic function using iterative, non-linear least squares fitting (Brown, 2001), with a coefficient of determination  $R^2=0,995$ . Fig. 6 shows the resulting survival rate profile, determined by the logistic curve with  $t_0=16.27$ ,  $\beta=0.23$  and  $\alpha=1.03$ .

After cars are retired from the stock according to age, the number of new registered cars is calculated using Eq. (3). The number of new vehicles of each category is defined according to some considerations. As shown in Fig. 7, fuel type share is based on the historical trend, where diesel vehicles have increased in recent years at the expense of petrol cars.

The evolution of engine-size share in new registered cars is based on income elasticities shown in Table 2. Finally, new registered cars are distributed in the stock according to age derived from the year of manufacture. The new registered cars contain mainly new cars but also some second-hand imported vehicles. The share of new registered cars is assumed to remain constant from 2013.

### *Mileage*

The mileage forecast for each fuel type, age and engine size starts with a top-down calculation of the total car fleet activity. Once again, income elasticity of demand (IED) and price elasticity of demand (PED) shown in Table 1, in combination with GDP growth ( $\Delta GDP$ ) and oil price growth ( $\Delta OP$ ), are used to forecast the activity, expressed in vkm:



$$Activity(t) = Activity(t - 1) \cdot (1 + \Delta GDP(t) \cdot IED), \cdot (1 + \Delta OP(t) \cdot PED) \quad (8)$$

Subsequently, average car mileage is obtained using activity and overall stock data. After that, a three-level process using activity and disaggregated stock is initiated to obtain mileage for each car category. First, the average mileage for diesel and petrol cars is calculated using a fuel weighting factor for each considered car category. Then, the average mileage according to fuel type and engine size is calculated by applying engine-size weighting factors, and finally, vintage weighting factors are applied to obtain the disaggregated mileage for a given year. Weighting factors are deduced from 2013 mileage profiles (Section 2.1.2) and considered constant up to 2050.

### 2.3 Local sensitivity analysis

The forecast model presented in this paper is intended as a reference scenario to be compared with alternative futures based on energy policy strategies. Although the main purpose of the model is not to forecast an exact value of energy consumption, uncertainties within the model must be examined to make it more reliable and to inform of any possible variability in its results. An important source of uncertainty in the model is associated with input parameters, as some are estimates, forecasts or observed values from other countries.

A sensitivity analysis (SA) has been performed to characterise how model outputs respond to changes in inputs and determine the most sensitive parameters. This allows us to (a) study the variability in the model's results originating from uncertainty in the input parameters, and (b) obtain information about factors with higher energy-consumption saving potential, which are related to the most sensitive parameters. Sensitivity analysis can be performed using various approaches, ranging from simple one-factor-at-a-time methods to more comprehensive approaches, usually based on Monte Carlo methods (Uusitalo et al., 2015). Local sensitivity analysis has been performed using finite-difference approximation based on central differences (Saltelli et al., 2000), a method previously applied in multiple modelling approaches, including car stock (Bandivadekar and Cheah, 2008) and housing stock models (Cheng and Steemers, 2011; Firth et al., 2010; Kavgic et al., 2013). This method assigns initial values (i.e. nominal values) to input parameters based on the data described in Section 2.1 and Section 2.2. Then each input parameter is subjected to a small change, while other input parameters are kept constant to their nominal value. Any changes in the output are used to calculate sensitivity coefficients. They represent partial derivatives of the output with respect to input parameters around their nominal values. For a model with  $m$  input parameters and a single output, the sensitivity coefficients can be calculated as:

$$\frac{\partial y}{\partial k_j} = \frac{y(k_j + \Delta k_j) - y(k_j - \Delta k_j)}{2 \cdot \Delta k_j} \quad j=1, \dots, m \quad (9)$$

where  $y$  is the output variable,  $k_j$  is the  $j^{th}$  input parameter, and  $y(k_j + \Delta k_j)$  and  $y(k_j - \Delta k_j)$  denote the value of  $y$  when the input parameter  $k_j$  is increased and decreased respectively by  $\Delta k_j$ . The accuracy of the sensitivities calculated depends on the parameter change  $\Delta k_j$ . Too large parameter change would damage the assumption of local linearity, while too small change can generate a high round-off error. Following the recommendations in Saltelli et al. (2000), a 1% perturbation is used in this study.

In this work, fourteen input parameters ( $m=14$ ) are considered and a single output variable, final energy consumption, is taken, which is evaluated at three points in time ( $t=3$ ) to determine near- (year 2020), mid- (year 2030) and long-term (year 2050) sensitivities. Normalised sensitivity

coefficients ( $S_{j,t}$ ) are calculated to make sensitivity results independent of the units of the model and to allow comparison between the effects of different input parameters.  $S_{j,t}$ , which represent the percentage change in output variable as a result of a one percentage change in input parameters, are given by:

$$S_{j,t} = \frac{k_j}{y_t} \cdot \frac{\partial y_t}{\partial k_j} \quad j=1,\dots,14 \text{ and } t=2020, 2030, 2050 \quad (10)$$

In addition, a superposition test is performed to analyse whether the combined effect of variability in the input parameters is equal to the sum of the effects of the individual changes. If this test is successful, the variability in the output caused by changes in several input parameters at the same time can be estimated with the calculated  $S_{jt}$  values.

### 3. Results and discussion

#### 3.1 Private car fleet energy consumption in 2013

Andorra's car fleet energy consumption in 2013 is calculated using Eq. (2). Fig. 8 shows the total final energy consumption for each car category. Its profile is similar to that given in Fig. 2, but with a proportionally lower contribution of old vehicles. Table 3 explores the proportional differences among the stock and the final energy in greater detail, comparing the share of stock and the total final energy according to fuel type, engine size and vintage. It can be observed that large-sized diesel engines and new vehicles have a higher contribution to energy than to stock. In the case of diesel engines and new vehicles, despite having a lower SEC than petrol and old cars, it is superposed by its higher mileage. The largest engines show the highest increase between analysed stock and energy shares, due to the combination of their higher SEC and mileage than other car engine sizes.

The total energy consumption of the car fleet in 2013 is 2083 TJ, which when expressed in volume of fuel represents 38.3 and 17.4 million litres of diesel and petrol, respectively. According to the results and official fuel imports for 2013 (Department of Statistics, 2014), the private car fleet is responsible for 45.4% of fuel imports related with transport. Transportation sector in Andorra is entirely focused on road transport, so the remaining imports are mainly distributed among motorbikes, buses, freight transport and fuel tourism. A lower fuel price in Andorra than in its neighbouring countries (Spain and France) and the high number of visitors entering the country by car suggest that fuel tourism could have important weight in national fuel imports. In fact, fuel tourism is a fundamental factor in Andorra's current and future energy consumption, not covered by this paper but that will be discussed in detail elsewhere.

#### 3.2 Reference scenario

Fig. 9 shows historic and projected new registered cars. Before the base year, the data is shown in an aggregated form, because no detailed information is available. In contrast to other transport stock models, where new sales are directly forecasted (Bandivadekar and Cheah, 2008; Daly and Ó Gallachóir, 2011a), the model forecasts overall stock and retirements, and then calculates new registrations using Eq. (3). This means that, similar to the historical new registered cars, the forecast has a non-smooth profile as opposed to the considered trends in economic development and fuel prices. New registrations grow rapidly in the short term, rising around 98% in 8 years (i.e. from 2013 to 2021). Their growth then levels out until 2040 when a new increase can be observed. Nowadays, Andorra has an old car fleet due to declining sales in recent years. Increasing car retirements are forecasted for the near term according to the stock

structure and the country's survival profile. As a consequence, boosted by the increase in stock, accelerated growth in registrations is expected.

As shown in Fig. 10, stock grows by 41% between 2013 and 2050, driven by GDP and fuel prices. It represents an average increase of 1.1%, which can be considered moderate compared with an annual growth of 1.9% between 2000 and 2013. Nearly 50% of car retirements in the coming years are expected to be with petrol cars due to the stock vintage profile. On the other hand, diesel vehicles dominate new registrations (77% in 2013), with a predominant weight of medium-sized engine cars (50% in 2013). These factors, combined with dieselisation and the increase in registrations of large-sized engines, lead to a stock where petrol and small-sized engine cars would have a marginal weight in 2050.

Fig. 11 shows the projected mileage and car fleet activity. The latter is expressed in million kilometres per year and grows by 33.1% until 2050. Future trends in the composition of the stock also drive the total activity of each car category. The slightly higher increase in stock than in activity leads to a decay in average mileage per car of 5.8% during the whole period (i.e. 0.16% per year).

Despite the projected increase in stock and activity, car fleet energy demand decreases by 17.2% until 2032. The expected development in fuel economy, new registrations and old car retirements are responsible for this improvement. After that year, energy demand grows by 0.3% per year on average, resulting in an overall decline over the whole 37-year period of 12.6%. The contribution of each car category to the total energy demand can be observed in Fig. 12. It shows that in 2050 the demand for petrol reduces significantly, representing only 11.3% of total energy. In parallel with the increase in stock, medium-sized engine diesel cars experience the highest rise in energy demand. Its demand share grows from 36.1% in 2013 to 52.1% in 2050.

### *3.3 Sensitivity in the final energy consumption forecast*

Local sensitivity analysis has been conducted on the model by varying fourteen important parameters and examining the effect on the fleet's final energy consumption at three points in time ( $t=2020, 2030$  and  $2050$ ). Input parameters and their nominal values ( $k_j$ ) are shown in Table 4. Normalised sensitivity coefficients ( $S_{jt}$ ) are also displayed, illustrating the sensitivity of the model output as a result of a one percentage change in input parameters.

Greater sensitivities are observed in the on-road factor, as it works as a direct multiplier in the model. Accordingly, significant uncertainty persists for a reliable estimate of this parameter. The possibility of a future increase in this factor, as reported in literature (Mock et al., 2014; Zachariadis, 2006), alerts about the interest of focusing future research on studying this trend. Fleet energy consumption is also quite sensitive to future new car SEC, increasing its sensitivity over time as more new cars replace existing ones in the current fleet. Furthermore, GDP growth and elasticity of activity with respect to GDP are among the most sensitive parameters. Large  $S_{jt}$  values in all parameters that exclusively influence fleet activity show the importance of this factor in fleet energy consumption and therefore, in defining transport energy strategies.

In general, and as expected, greater sensitivities are experimented for more distant futures, reflecting the increase in uncertainty when forecasting long-term scenarios. A notable exception is observed in the survival rate, where the highest sensitivity value is found in the near term, a consequence of the high number of expected retirements and new registrations in the coming years due to the vintage nature of the car fleet. This is indicative of the importance of renewing the stock in the coming years to minimise fuel consumption in Andorra.

### 3.3.1 Linearity and superposition test

The local sensitivity experiment conducted in this study illustrates the sensitivity of the model by changing the input parameters over small intervals around its nominal values. The variations of the output produced by larger changes in inputs can only be determined if the input-output relationship is demonstrated to be linear (Saltelli et al., 2000). The principle of linearity is tested by approximating the input-output relationship through a first-order polynomial. The range of input change around the baseline case is defined to cover a wide range of reasonable input parameter values. In Table 5, the coefficients of determination ( $r^2$ ) show, for the eight input parameters with the highest sensitivities, how accurately a linear function describes the relation between the input parameter change and the effect on the output (i.e. high  $r^2$  values favour the application of the principle of linearity in all input parameters under study). Therefore, any changes in the final energy consumption caused by larger changes in inputs can be estimated from the  $S_{jt}$  values displayed in Table 4 and Eq. (11):

$$\Delta y_t = S_{jt} \cdot \Delta k_j \quad (11)$$

The superposition test applied in this paper involves building scenarios by simultaneously varying different input parameters. The combined effect of the input changes obtained using the model and the sum of the effects of the individual changes calculated with  $S_{jt}$  values are then compared. Four scenarios have been designed, not only to check superposition, but also to explore the possible variability of the model with respect to the reference scenario results presented in Section 3.2. Similarly, some general policy measures have been explored by analysing the scenario to provide an initial estimation of the potential energy savings through different strategies. The considered scenarios (i.e. S1 to S4), input parameter changes, and the results of the superposition test are shown in Table 5.

- S1 and S2 are the scenarios designed to represent the greatest expected variability of the results with respect to the reference scenario. In S1, the input parameters have been changed to obtain the maximum positive deviation (i.e. energy consumption increase). On the other hand, S2 estimates the maximum expected negative variation (i.e. energy consumption reduction). Changes in elasticities are defined by adding or subtracting one standard deviation as derived from Goodwin et al. (2004). It can be observed that standard deviations are large in relation to the means, as the estimates come from a wide range of sources and contexts. The on-road factor is changed considering theoretical extreme values in Andorra (Traveset-Baro et al., 2015), being the highest one obtained in a scenario of aggressive driving style, and the lowest one when calm driving is considered. The assumptions in the variations of other parameters have been made in order to represent a coherent maximum change according to the nature of the parameters.
- S3 and S4 represent scenarios where a broad estimation of the potential energy savings related to different policy strategies has been defined. The effect of energy measures is predicted, considering changes only in parameters where energy policies have some influencing capacity. As an example of this, it is considered that local energy policies in Andorra do not directly influence oil price growth, new car SEC or national GDP growth. In S3, the potential effect of behaviour-focused policies is assessed, moderating the value of elasticities related to total car activity and considering the theoretically lowest on-road factor. S4 represents the effect of technology-focused policies, varying the cars' survival rate and the share of diesel cars in new registrations.

The effect of the combined changes derived from the model and the sum of the individual changes using  $S_{jt}$  have been compared in a near, mid and long term. It can be observed that the principle of superposition is only met when the output (final energy consumption) is analysed in the near term. When the time horizon is longer, greater differences between the model and the  $S_{jt}$  calculations are observed, showing that the individual effects are not simply superimposable. The non-superimposable property hinders the development of a simpler model to estimate final energy consumption in a mid and long term. On the other hand, variations of the output in relation to the variability in input parameters can be suitably estimated in a near term using calculated  $S_{jt}$  values.

These scenarios show increasing variability over time with respect to the reference scenario and a higher positive (in S1) rather than negative (in S2) potential change. In relation to energy strategies, behavioural policies have greater potential than policies focused on technology. It can be observed that improvements provided by technological policies decay in a medium and long term, probably linked to the expected standstill of energy-efficiency improvements in diesel and petrol cars after 2020 (Pasaoglu et al., 2012). In any case, these results suggest that in order to achieve significant savings in transport energy consumption, it is essential to employ policies focused on limiting car activity or promoting a more moderate driving style. In this regard, it should be noted that in this study, only changes in existing technologies in the current fleet have been assessed. The introduction of new vehicle technologies in the Andorran car fleet is not discussed here, but will be addressed in detail elsewhere.

#### **4. Conclusions and policy implications**

This paper presents a private car transport energy model adapted to account for data scarcity, such as in the case of Andorra. It can be classified as a bottom-up simulation forecasting model, where energy demand is driven by the technological composition of the car stock and the behaviour of private car users. The resulting model demonstrates how a useful decision-making tool can be implemented in the absence of significant data.

The model shows that the private car fleet in Andorra is responsible for 45.4% of fuel transport imports. It highlights the importance of this sub-sector in the country's energy system and contributes to improve the understanding of the technological and behavioural drivers of energy consumption. The reference scenario predicts an important increase in vehicle sales in the near term caused by the current aged car fleet and the optimistic prospects about GDP growth. Car activity and stock is also expected to increase during the period forecasted. Nonetheless, the forecast shows a moderate decrease in car fleet energy consumption, driven by the expected improvements in car stock fuel economy. Andorra does not currently have any targets regarding energy consumption in general, or transport, in particular, and it is a fundamental issue to have access to detailed models in order to define reasonable, socially and economically consistent goals.

The paper develops different scenarios based on the variability of key input parameters. This methodology is useful in addressing some model uncertainties, a fundamental step in giving policymakers greater confidence about forecast results. In addition, sensitivity analysis results can be used to prioritise further research by addressing the estimates of those parameters that have the greatest effect on the output of interest. When linearity and superposition is demonstrated, sensitivity coefficients can be used to build scenarios for assessing the variability of the model more easily than doing multiple simulations. This can be useful for policymakers to develop quick estimations of the possible variability of the main results due to changes in the

input parameters, without needing to simulate the entire model. The superposition results show that this principle can only be applied in the model in the near term (i.e. until 2020), so the entire model needs to be simulated in the mid and long term.

As mentioned earlier, the results in the baseline scenario must be interpreted as a reference case to be compared with alternative scenarios, rather than to be taken as a deterministic view of the future. The case study presented in this paper provides a broad estimate of the potential energy savings achieved in Andorra, however the objective is to use it to support national policy decision-making processes by quantifying the impacts of specific energy policy measures. The next steps in the modelling process involve including alternative car technologies (i.e. electric, hybrid and compressed natural gas vehicles), incorporating the remainder of vehicles present in the road transport sector (i.e. motorbikes, public transport and freight transport) and developing an estimate of energy imports related to fuel tourism.

Quantifying the potential of energy policies in transportation sector is of particular interest in defining coherent energy-saving targets. Andorra, as a party of the United Nations Framework Convention on Climate Change, has recently submitted its intended self-determined contribution, establishing a reduction of GHG emissions by 37% as compared to a business-as-usual scenario by 2030. The model developed in this paper is particularly useful in exploring the potential of the transportation sector's contribution in achieving this goal.

## **Acknowledgements**

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## Figures

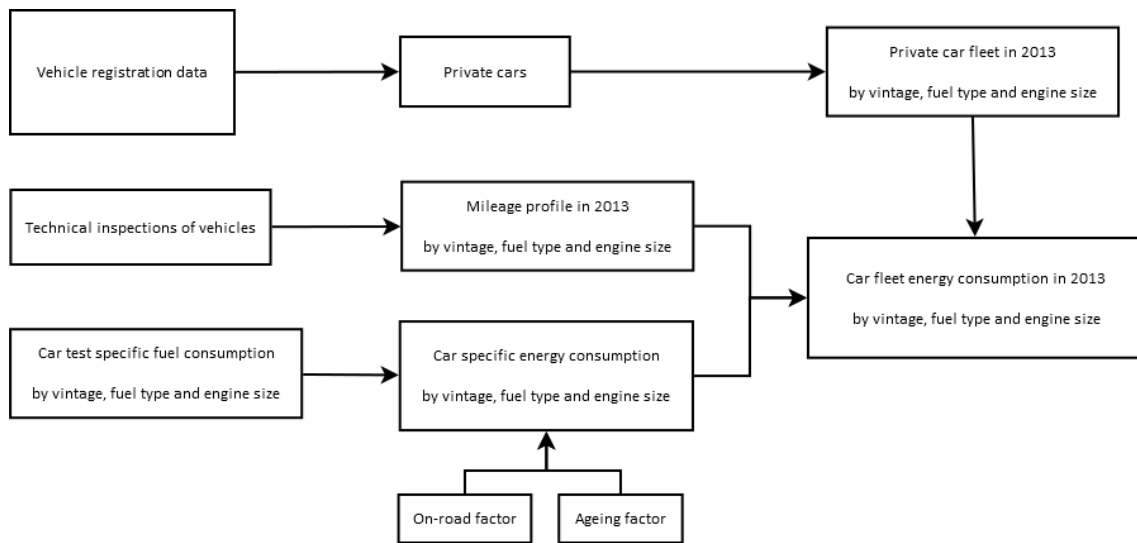


Fig. 1. Overall structure of the technological car stock model

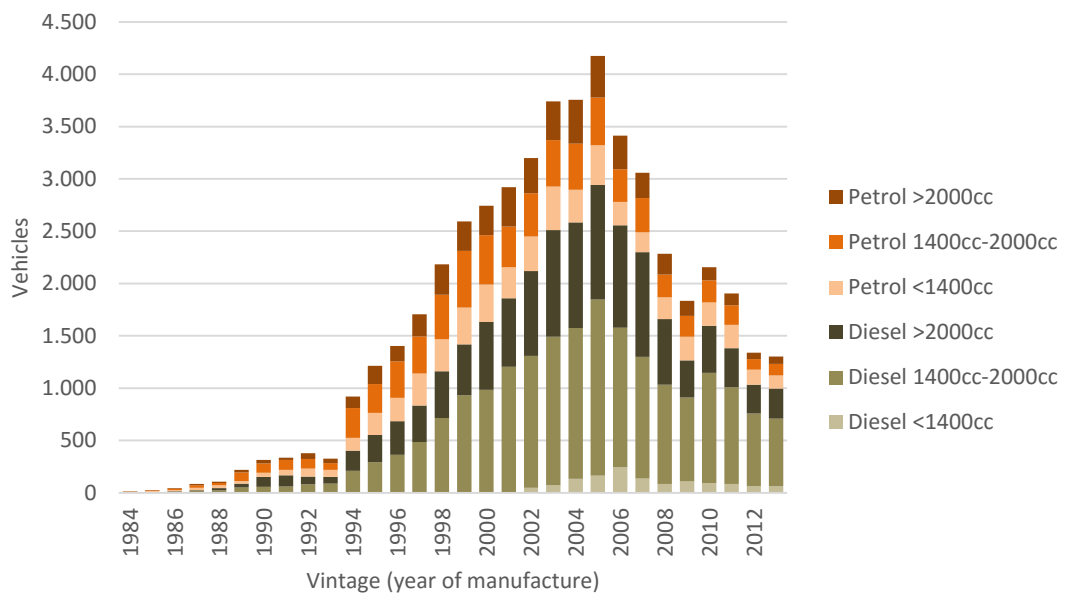
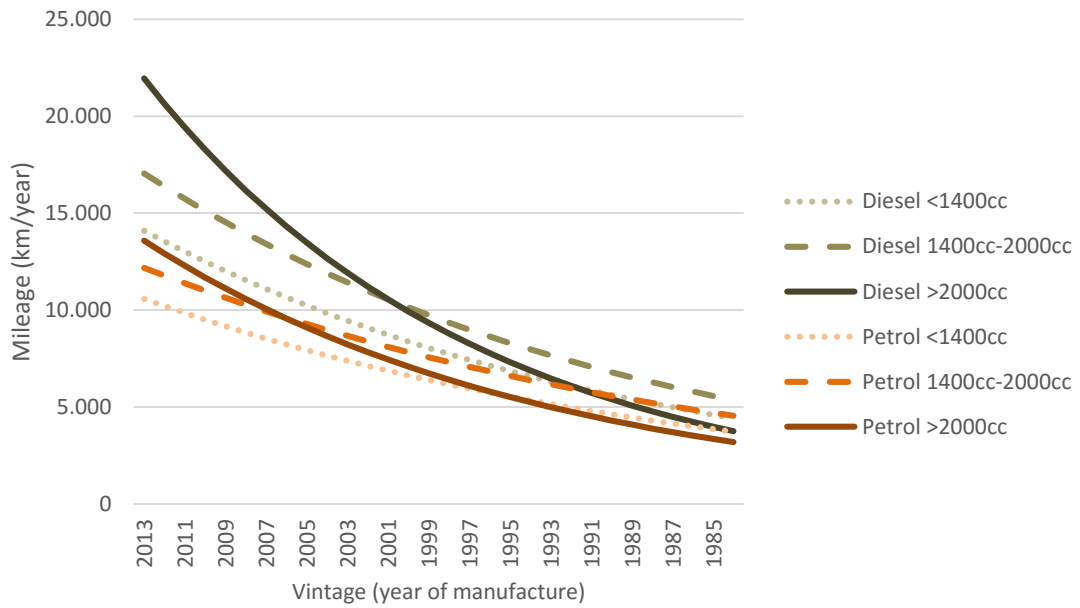
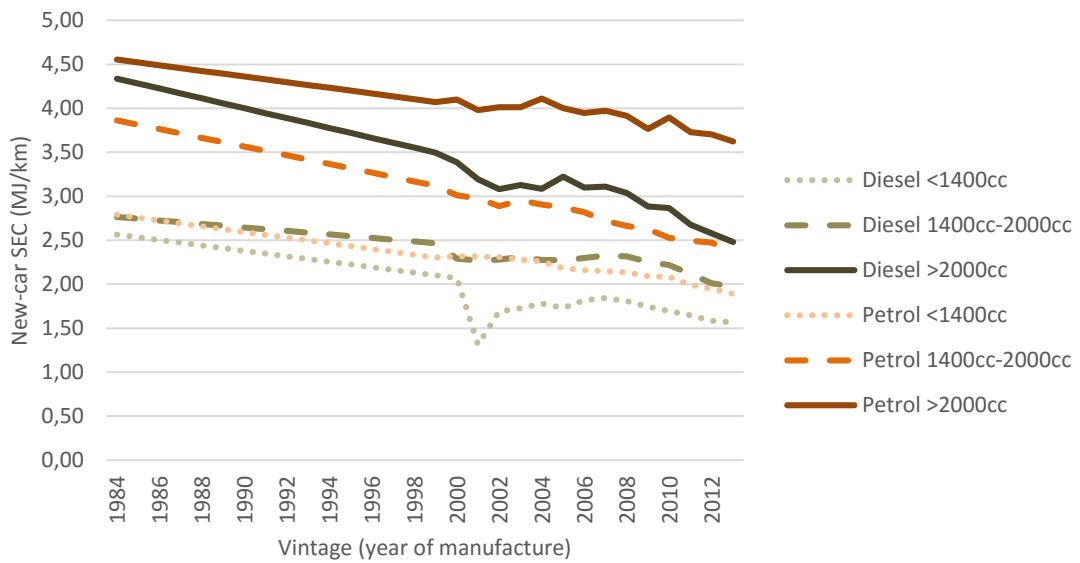


Fig. 2. Andorra's 2013 private car fleet by fuel type, engine size and vintage



**Fig. 3.** Average mileage profile in 2013 by car category



**Fig. 4.** New-car specific energy consumption for each passenger car category

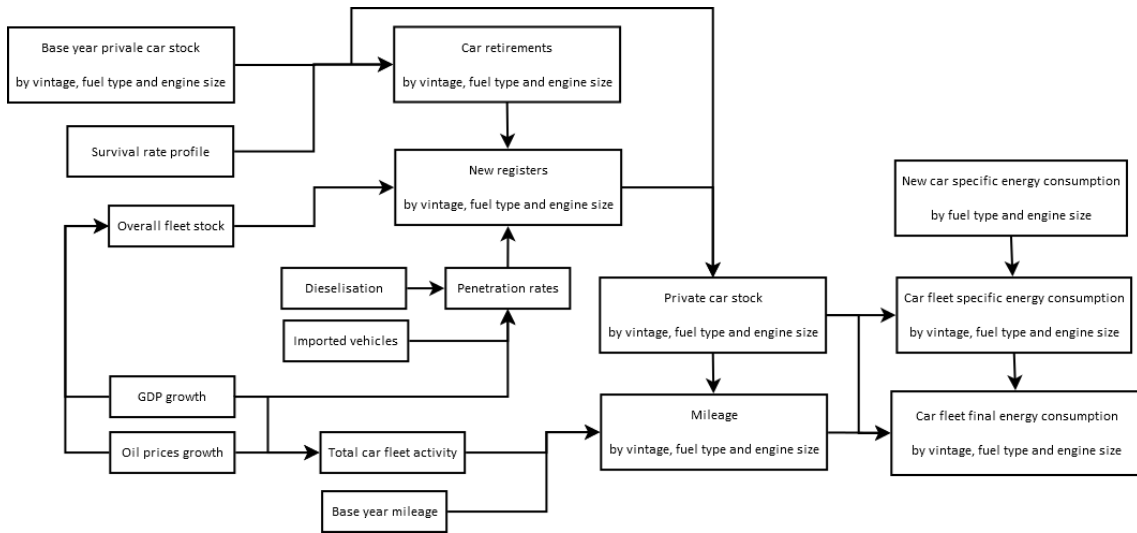


Fig. 5. Model forecast overview

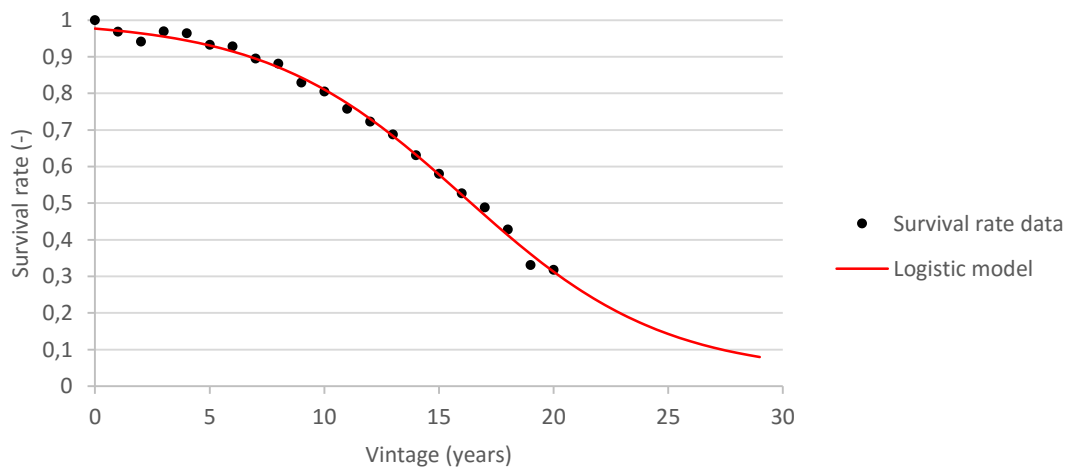
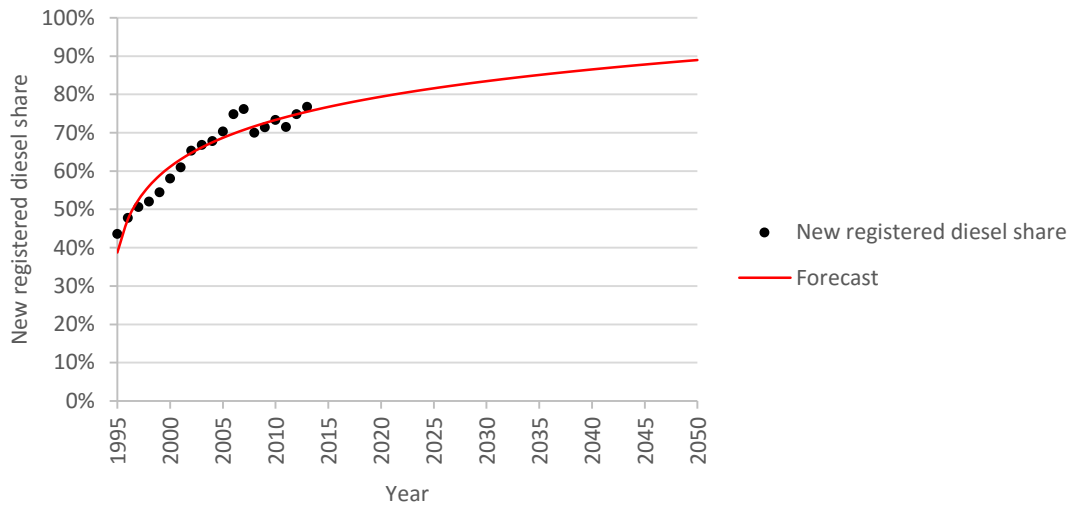
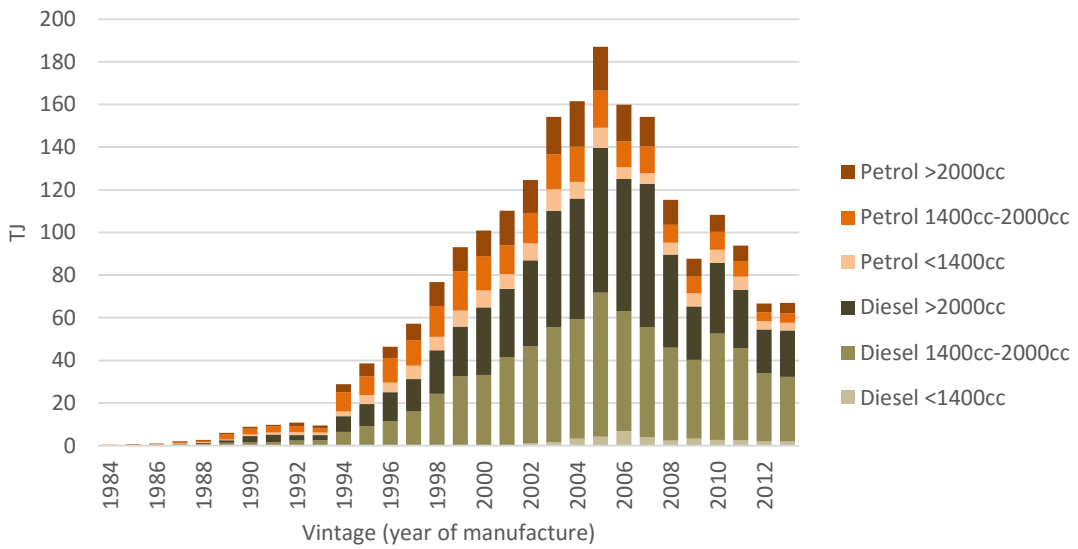


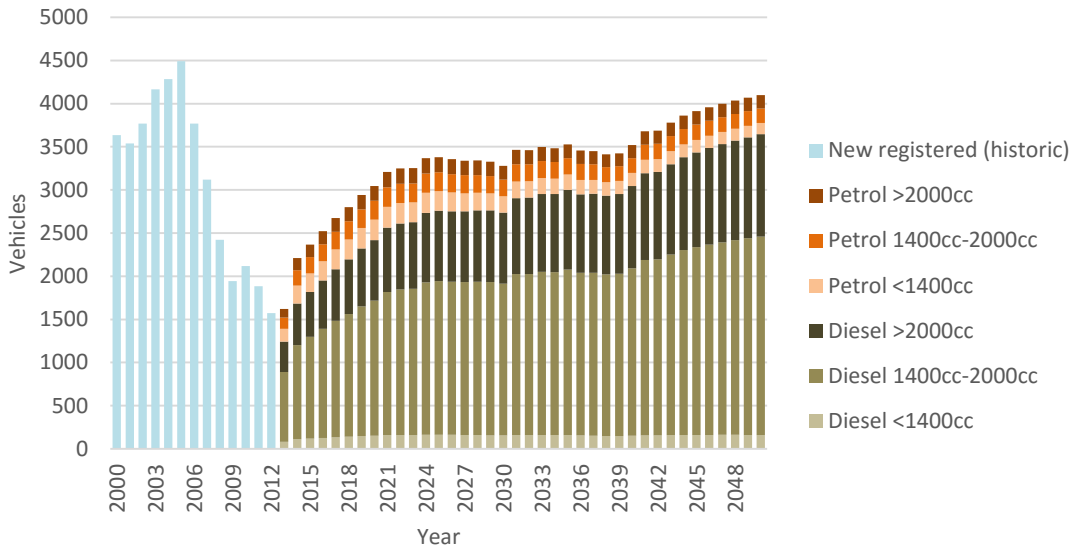
Fig. 6. Survival rate profile determined using a logistic curve fitting



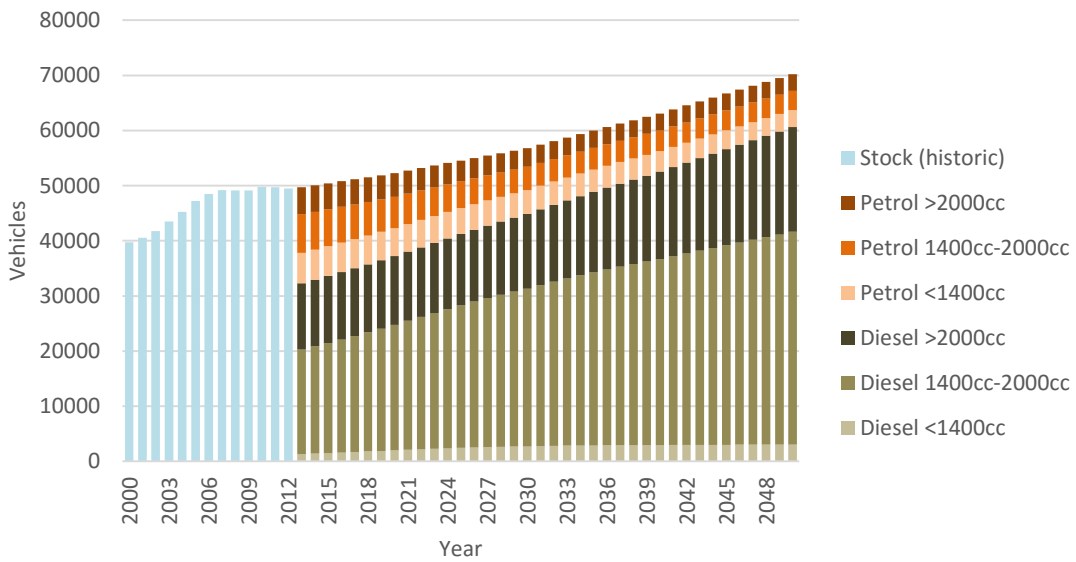
**Fig. 7.** Dieselisation trend for new registered cars in Andorra and forecast up to 2050



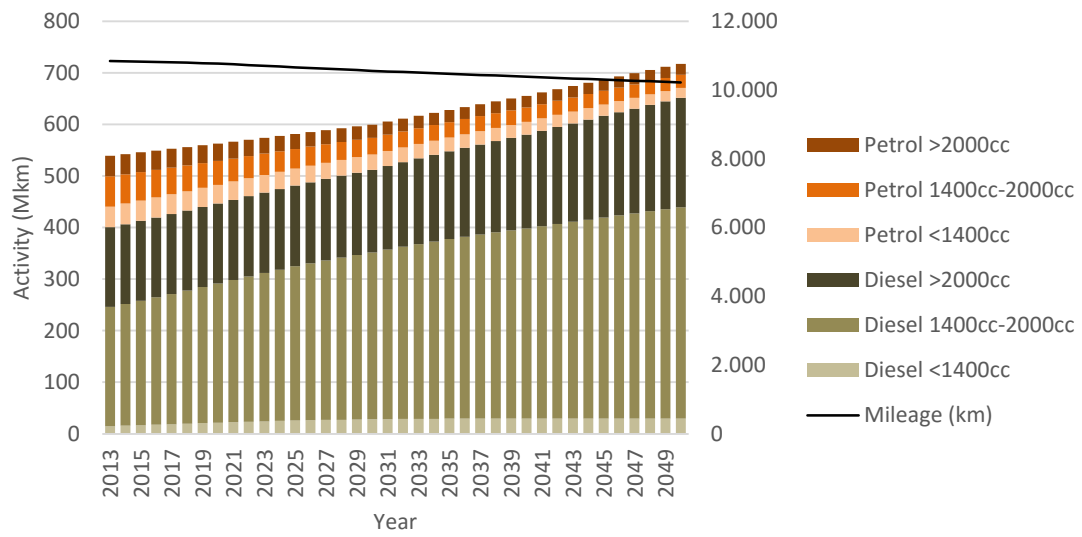
**Fig. 8.** Final energy consumption of private car fleet in 2013



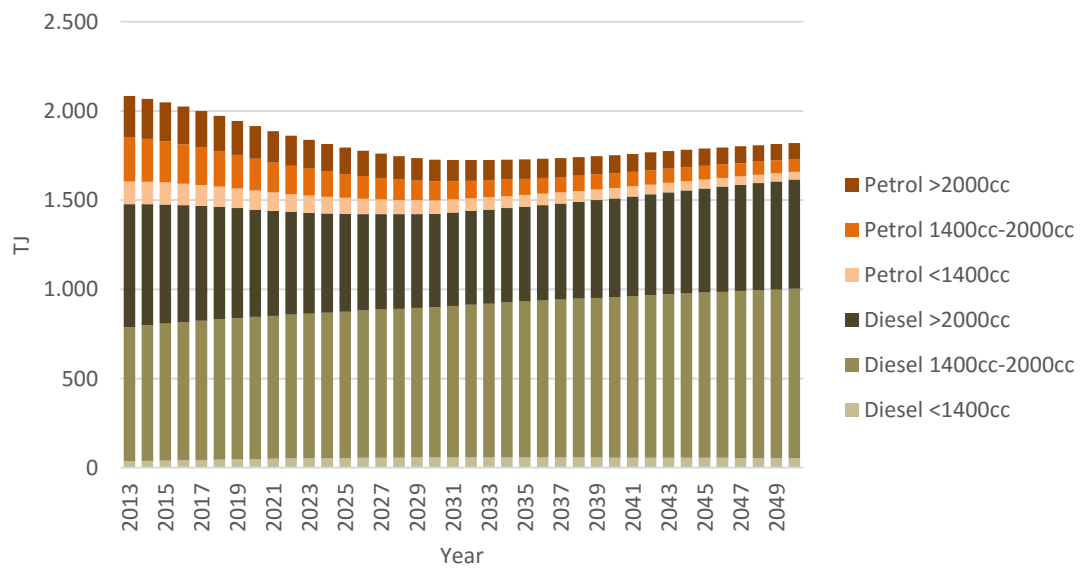
**Fig. 9.** Historic and projected registered cars



**Fig. 10.** Historic and projected car stock



**Fig. 11.** Projected car fleet activity and average mileage



**Fig. 12.** Projected car fleet final energy consumption by car categories

## Tables

Elasticity	Fuel price	Income
Car fleet activity	-0.29	0.73
Car stock	-0.25	0.81

**Table 1.** Car stock and activity elasticities with respect to GDP and oil price considered in the model

Elasticity	Income
<1400 cc	-0.2
1400–2000 cc	0.5
>2000 cc	0.8

**Table 2.** Engine-size elasticities with respect to GDP considered in the model

Share of total		Stock (%)	Final energy (%)
<b>Fuel type</b>	Diesel	65	71
	Petrol	35	29
<b>Engine size</b>	<1400 cc	13.7	7.9
	1400 cc-2000 cc	52.2	48.1
	>2000 cc	34.1	44
<b>Vintage</b>	0-9 years	50.8	57.6
	10-19 years	45.5	39.9
	20-30 years	3.7	2.5

**Table 3.** Share of stock and final energy according to fuel type, engine size and vintage

Input parameter	$k_j$	$S_{j2020}$	$S_{j2030}$	$S_{j2050}$
GDP stock elasticity (-)	0.81	-0.011	-0.009	-0.004
GDP activity elasticity (-)	0.73	0.052	0.167	0.398
GDP engine size elasticity (<1400 cc) (-)	-0.2	0.000	0.000	0.001
GDP engine size elasticity (<1400–2000 cc) (-)	0.5	0.000	-0.002	-0.008
GDP engine size elasticity (>2000 cc) (-)	0.8	0.000	0.005	0.019
Oil price stock elasticity (-)	-0.25	0.001	0.003	0.001
Oil price activity elasticity (-)	-0.29	-0.009	-0.062	-0.115
Survival rate – Median lifetime ( $t_0$ ) (years)	16.3	0.187	0.082	0.037
On-road factor	1.396	1.000	1.000	1.000
Ageing factor (%)	0.3	0.029	0.025	0.025
GDP growth per year (%)	1.1*	0.041	0.162	0.407
Oil price growth per year (%)	0.4*	-0.007	-0.059	-0.114
New registered diesel share per year (%)	76*	-0.052	-0.108	-0.147
New car SEC (MJ/km)	Different values	0.436	0.884	1.000

**Table 4.** Nominal values and normalised sensitivity coefficients for the considered input parameters. For those parameters that change over time (i.e. identified with an asterisk), a 1% variation has been applied to the forecasted value for each year. The values shown correspond to year 2014



	Input parameters	Linearity test			Superposition test			
		Coefficient of determination $r^2$			Variability with respect to BAU (%)			
		2020	2030	2050	S1	S2	S3	S4
	GDP activity elasticity	0.9999	0.9991	0.9943	65.75	-65.75	-65.75	0.00
	Oil price activity elasticity	1	0.9999	0.9995	-100.00	100.00	100.00	0.00
	Survival rate (to median lifetime)	0.9896	0.9471	0.9776	30.00	-30.00	0.00	-30.00
	On-road factor	1	1	1	6.88	-7.02	-7.02	0.00
	GDP growth per year	0.9999	0.999	0.994	50.00	-50.00	0.00	0.00
	Oil price growth per year	1	0.9999	0.9995	-50.00	50.00	0.00	0.00
	New registered diesel share per year	0.9979	0.9989	0.9992	-10.00	10.00	0.00	10.00
	New car SEC	1	1	1	10.00	-10.00	0.00	0.00
<b>Final energy consumption (t)</b>								
2020	Combined changes (%)				26.03	-21.86	-10.95	-5.48
	Sum of individual changes (%)				24.09	-24.23	-11.33	-6.12
	Difference (%)				-1.94	-2.38	-0.38	-0.64
2030	Combined changes (%)				62.46	-37.22	-21.76	-3.24
	Sum of individual changes (%)				47.53	-47.67	-24.23	-3.55
	Difference (%)				-14.93	-10.45	-2.47	-0.31
2050	Combined changes (%)				144.66	-53.65	-36.27	-2.50
	Sum of individual changes (%)				83.15	-83.29	-44.68	-2.59
	Difference (%)				-61.50	-29.64	-8.41	-0.09

**Table 5.** Linearity and superposition test results. The range of the input change in the linearity test is  $\Delta k_j = \pm 50\%$ , except for the input parameter *New registered diesel share per year* where  $\Delta k_j = \pm 10\%$  is assumed (with a variation of  $\pm 50\%$ , more than 100% of diesel share would be reached)