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Technology-behavioural modelling of energy innovation diffusion in the UK

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ABSTRACT

The diffusion of energy saving technologies is an important part of UK energy and climate policy. Innovation diffusion can be influenced by both technological and behavioural factors. A computational model is presented to capture how changing technology attributes can influence consumer adoption. The UK vehicle market is case analyzed showing how efficiency improvements in advanced internal combustion engine (ICE) vehicles might affect future diffusion of alternative fuelled vehicles (AFVs) which is not often considered in the debate on AFV competitiveness. Scenarios are developed for mass and early market adopters to account for consumer heterogeneity. Simulation results indicate that if AFV performance can keep pace or exceed ICEs this will positively affect AFV diffusion despite increasing competition from ICEs on attributes that currently favour AFVs, such as fuel economy and carbon emissions. However, much of the gains are made at the expense of diesels rather than petrols that also benefit from improved performance. Additional policy measures will likely be necessary to induce rapid AFV diffusion.

1. Introduction

The three central challenges for energy policy stated in the UK Energy White Paper are: (1) the threat of climate change, (2) declining domestic oil, gas and coal production and, (3) the need for energy infrastructure investment [1]. The UK was the first country to announce a major long-term carbon emission reduction target of 60% by 2050, which has now been reset at 80%. Energy security has also re-emerged as an important UK policy driver due to depletion of domestic fossil fuel resources and increasing reliance on energy imports from potentially politically unstable suppliers [2–4]. UK coal production peaked in 1913. Since 1973, coal production has declined by 80% largely due to phasing-out of government subsidies in the mid- and late-1980s. Oil production peaked in 1999 at 143 million tonne oil equivalent (Mtoe). From 1999 to 2004, oil production declined by 30% as the UK Continental Shelf (UKCS) fields matured. Gas production also peaked in 2000 at 97.5 Mtoe declining by >11% in 2004 [3]. Consequently, in 2004, the UK became a net fossil fuel importer for the first time since 1991. With North Sea production falling and growing domestic demand, the UK will likely continue to be a net importer in the foreseeable future. These energy challenges are set against UK targets to shift towards a low carbon transport system while maintaining economic competitiveness and growth. The UK transport sector is currently 99% dependent upon liquid fossil fuels with an expected 80% of all fossil fuels imported from overseas by 2020 [2,4]. For UK energy policy, rapid diffusion of alternative fuel vehicles (AFVs) is a key strategy to decrease oil dependency and achieve deep cuts in carbon emissions by 2050 [2,5,6].

The transport sector is a major source of unsustainable energy use currently contributing ~20–25% global CO_2 emissions [7]. Energy use and CO_2 emissions in transport are closely linked to vehicle engine efficiency i.e. fuel requirement per unit distance travelled and the relative carbon content of fuel e.g. gasoline, biofuel, and electricity. Improved fuel economy through advancements in vehicle technology will reduce transport energy intensity [8]. Although the potential benefits of AFVs have been demonstrated many uncertainties exist over the scale and timing of their market diffusion [9–11]. Importantly, it is not often considered how technological advances in incumbent technologies will impact upon the competitiveness of AFVs. Much of the literature focuses on the potential benefits of AFVs without considering evolving technological performance and market competition from the consumer's perspective.

Future trends in passenger car markets are often modelled as part of large economy-wide models which can be characterized as (1) supply-driven forecasts that assume aggressive industry investment and targeted policy interventions or (2) demand-driven forecasts that assume rapid consumer adoption based on changes in economic parameters such as reduced price differentials between competing technologies [5,12]. Much of that work involves sophisticated approaches that have given insight into large-scale system behaviour focusing on different technological pathways. However, there is often an implicit assumption that massive investments in supply will be met by consumer demand, or that rapid consumer adoption will be met by sufficient supply. This paper builds on previous modelling work, but also departs

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by specifically focusing on the underlying dynamics between technological performance and consumer preferences in the context of innovation diffusion in the UK. A model that captures the technological and behavioural aspects of innovation diffusion is developed and scenarios are used to assess mass and early market adopters. There is a specific focus on how advances in incumbent technologies will affect the competitiveness of AFVs, which is not well explored in the literature. This paper proceeds as follows: outline of the technological and behavioural aspects of innovation diffusion, derivation of a 'techno-behavioural' model of diffusion, model calibration and scenario development, and simulation results and discussion.

2. Technological and behavioural aspects of diffusion

The spread of innovations is influenced by both technological and behavioural factors [13–15]. For example, innovations spread through society, while technologies improve over time. Individuals learn of innovations through social interactions with previous adopters, which in turn influence their own personal preferences for that innovation [16]. This is a type of social learning process that can positively influence the diffusion process [17]. Technologies also change and improve over time, which can increase returns to adoption and accelerate diffusion [17]. Technological improvements, termed technology learning is an empirical relationship between technology cost, c and the cumulative growth in stock, y observed to be a power law of the form,

$$c(y) = y^{-\alpha} \tag{1}$$

where the exponent, α is the rate of improvement, termed the progress ratio, $2^{-\alpha,}$ which is the factor by which costs decrease with each doubling of cumulative stock. This empirical relationship has been observed for a number of energy technologies including installed wind capacity, photovoltaic (PV) cells among others [18]. The growth in stock however, is also a function of increasing consumer adoption, which is typically not accounted for in the analysis of technological learning and diffusion. But both social and technological factors interact to influence the diffusion process.

Mathematical modelling and forecasting the diffusion of technological innovations have been well established since the seminal works of Rogers [16] and Bass [19]. Diffusion theory can explain the factors that determine the rate at which new energy technologies spread through society [20]. Diffusion theory has typically been applied to consumer durable goods but has found less application to new technologies with environmental benefits. Usha Rao and Kishore [21] argue for the need to build up experience in applying diffusion models to renewable energy technologies (RETs). They indicate that while learning curves (Eq. (1)) have been widely used for economic considerations it is important to consider how policy, social, and technological factors can influence the diffusion process. Although diffusion theory has been applied to conventional vehicles, new vehicle technologies particularly low emission vehicles face similar challenges as RETs such as high capital investment and lack of a level playing field while having similar environmental and energy reduction benefits.

However, the key difference between RETs and vehicle technologies is that diffusion of the latter will depend upon individual consumer preferences [22]. Pacala and Socolow's [23] stabilization wedges target energy-demand behaviour as one of the most cost effective options for decreasing CO_2 emissions. This points to the important, but less understood interplay between how consumer behaviour, particularly purchasing decisions affects the market diffusion of energy-demand technologies, or how changes in those technologies can in turn influence consumer adoption. Although other studies have applied diffusion theory to AFVs they have focused more on system wide effects [24,25]. This paper addresses some of those gaps by developing a model that examines how changes in vehicle technology attributes and consumer preferences impact the cumulative build up of vehicle stock.

3. Deriving a technology-behavioural diffusion model

A bounded geometric growth model is developed to simulate an evolving vehicle market in single year time steps over the period 2000–2035. The model is applied to the UK passenger vehicle market and calibrated to 1999–2009 historical data given below. Simulations are used to analyze the rate of technology adoption, substitution, and decay of competing technologies within a single market. Growth of the total vehicle stock or market, *TVM* is given by the following difference equation,

$$TVM_n = [TVM_{n-1} * \Phi_{TVM}] + [TVM_{n-1} - (\lambda^* VAD)] \tag{2}$$

where, Φ_{TVM} is a growth parameter representing total market demand for passenger cars in each time step, n. This parameter can be adjusted to reflect macroeconomic, demographic and other transport demand trends. It is currently adjusted to UK macroeconomic forecasts of total vehicle passenger demand growth. Lambda, λ is a decay parameter representing stock scrappage, where a fraction of the total vehicle stock, TVM_{n-1} is subtracted at each time step, n. The scrappage rate, λ is calculated for each vehicle age segment within the total vehicle age distribution, *VAD*. This is based on passenger vehicle statistics showing the initial year of vehicle licensing starting in 1980 and the number remaining on the road in 2005 where a low fraction (~5%) of new vehicles (<3yrs) compared to a high fraction (~70%) of older vehicles (>13yrs) are scrapped [26].

The model currently uses the average scrappage rate across all vehicle age distributions calculated at ~14% and assumes it remains constant over the modelled period. Each vehicle technology is scrapped in proportion to its' share of the total vehicle stock (TVM) in each time step. The scrappage parameter is currently used to calibrate the model. Future analyses could disaggregate the scrappage function to simulate different policy interventions such as accelerating the scrappage rate of targeted vehicles, or future changes in technology durability that may increase the operational life of a vehicle. The total vehicle market, *TVM* is then disaggregated into individual vehicle technologies that compete against each other for market share. The diffusion of individual technologies is a function of both 'supply-push' and 'demand-pull' dynamics. This enters the model as the diffusion of individual vehicle technology stock, TVS_{jn} of technology j in year n given by,

$$TVS_{jn} = [TVS_{jn-1} * \Omega_{jn}] + [TVS_{jn-1} - (\lambda^* VAD)] * [P_{ijn}] \tag{3}$$

where Ω_{jn} is a parameter representing the growth rate of technology j in year n, exogenously set in the model. This parameter is used to calibrate the model to the UK vehicle stock. However, it could also be used to simulate industry investment, or targeted government policy for specific vehicle technologies representing a 'supply-push' dynamic in the model. Since the total vehicle market, *TVM* is comprised of individual technologies, TVS_j the growth of each individual technology is normalized to the growth of the overall market with the following normalization algorithm, N given by,

$$N = TVM_n / \sum_{j=1}^{k} TVS_{jn} \ldots k \tag{4}$$

$$TVS_{jn} = TVS_{jn} * N \tag{5}$$

resulting in,

$$TVM_n = \sum TVS_{jn} \tag{6}$$

The total vehicle stock, TVM_n therefore serves as an upper bound on the geometric growth of each individual technology at each time step, *n*. This results in diffusion curves with different inflection points simulating the phasing in and out of different technologies that compete against each other in a single market. Also, by normalizing the growth of all individual technologies to the total vehicle market where, $TVM = \sum TVS_j$ the model simulates market saturation effects from accumulation of individual vehicle technologies over time since, *TVM* acts as an upper bound on the growth of each individual technology.

Consumer adoption behaviour simulating 'demand-pull' dynamics is represented by individual preferences for technological attributes [16]. A mixed logit (ML) discrete choice-modelling (DCM) framework is used for evaluating consumer decision-making for adoption of vehicle technologies [27–29]. The probability to adopt is motivated by the perceived utility that a consumer derives from the technology based on individual preferences [30–32]. The random-coefficients structure of the ML is used because it captures heterogeneity in an individual's sensitivity to different attributes of a particular innovation, which is an important factor for adoption [16]. Consumer behaviour enters the model as a simulated probability function, P_{ijn} where the probability that consumer, *i* will select technology, *j* in year, *n* is,

$$P_{ijn} = \frac{e^{\beta' X_{ij}}}{\sum_{j=1}^{J} e^{\beta' X_{ij}}} \tag{7}$$

where X_{ij} is a vector of observed variables that represent technology attributes such as purchase price, fuel consumption, CO_2 emissions, etc. Beta, β is a vector of random coefficients that represent individual preferences or tastes for the observed attributes. If the vector of, β's are observed, P_{ijn} collapses to the standard multinomial logit model (Equation 7). However, if β is not observed preferences can be captured by a probability density, $f(\beta\ |\theta)$ where the functional form, $f(\cdot)$ is specified based on parameters, θ such as the mean, μ and standard deviation, σ. With this specification, P_{ijn} takes the form of an open integral,

$$P_{ijn} = \int L_{ij}(\beta) f(\beta|\theta) d\beta \tag{8}$$

which can be numerically integrated by Monte Carlo simulations using the following algorithm from [33]: Take a random draw, *R*, of β's from a density $f(\beta|\theta)$ such that,

$$(\beta_n) \sim f(\beta_n|\theta) \tag{9}$$

Calculate the conditional probability L_{ijn} as,

$$L_{ijn} = \frac{e^{\beta' X_{ij}}}{\sum_{j=1}^{J} e^{\beta' X_{ij}}} \tag{10}$$

Repeat *R* times such that,

$$P_{ijn} = \frac{1}{R} * \sum_{r=1}^{R} L_{ij}(\beta^r) \tag{11}$$

As *R* increases variance, σ decreases. While several density functions can be used for $f(\cdot)$ the normal and lognormal distributions are the most common [33–35]. A lognormal distribution is used to specify a beta (β) coefficient having the same sign (+/−) for all individuals. This allows the model to assume global preferential behaviour for specific vehicle attributes under different scenario assumptions. For example, a negative coefficient for purchase price is used assuming all consumers are negatively influenced to adopt from high vehicle costs, or early adopters can be simulated by giving preferential weighting for a low CO_2 emitting vehicle attribute such as battery electric vehicles (BEVs). The simulated probability, P_{ijn} is calculated for each technology, *j* in time step *n*. The probability that a consumer adopts, P_{ijn} is multiplied by the growth of each technology, TVS_{jn} for the corresponding technology, *j* in time step *n*, which conditions the rate of diffusion and cumulative growth of each technology, TVS_{jn} over the projection period (Eq. (3)). The model captures the interaction between individual preferences and technological attributes, how those factors may change, and the impact it has on total market diffusion.

4. Model data and scenario development

4.1. Model data and calibration

The model is calibrated to the UK medium size passenger car market and assumes it is representative of the total vehicle stock. Vehicles are selected based on the incumbent technology system and recent UK policy and industry trends towards AFVs. Technologies in the model include: petrol internal combustion engine (ICE), diesel-ICE, hybrid electric-petrol (HEV), plug-in hybrid electric-petrol (PHEV), pure battery electric (BEV), and hydrogen fuel cells (FC). Vehicle attribute data and normalized model input values are listed in Tables 1 and 2 respectively. The model is calibrated to historical UK data and used to develop a reference case scenario fully described in the next section.

The vehicle typologies in the model are representative of the same lower/upper medium class allowing for comparison. As a result, the model does not currently capture different vehicle classes where consumer preferences would likely differ, nor does it capture a consumer wanting to downsize or up-grade vehicle class. But the vehicles used are typical models now available on market, which allows for analysis of how consumers make trade-offs between technologies at the attribute level. Example vehicles in the model include: Petrol: 2011 Ford Focus, 4 cyl, 2.0 L, 140 hp; Diesel: 2011 Volkswagen Jetta, 4 cyl, 2.0 L, 115 hp; HEV: 2011 Toyota Prius, 4 cyl, 1.8 L, 134 hp; PHEV: 2011 Chevy Volt, 4 cyl, 1.4 L, 150 hp, Battery: 348 V, 16 kW h, Li-ion, Motor: 111 kW, 3-Phase Asynchronous, continuously variable transmission (CVT); BEV: 2011 Nissan Leaf, Battery: 360 V, 24 kW h, Lithium-ion (Li-ion), Motor: 80 kW DC Permanent Magnet, Brushless, automatic transmission (1 speed); and, FC: 2011 Honda FCX Clarity, Proton Exchange Membrane Fuel Cell (PEMFC), Battery: 288 V Li-ion, Motor: 100 kW DC Brushless.

Purchase prices are the manufacturer suggested retail price (MSRP) in 2011 US dollars (USD) and FC purchase price from ref [8,39]. All prices have been converted to Great Britain Sterling Pound (£) using August 2011 exchange rate of 1 GBP = 1.59421 USD. Running costs include fuel price, VAT and resource costs from ref [38] and updated with UK Fuel Duty from January 1, 2012: Ultra-Low Sulphur Petrol (61.0 p/L), Ultra-Low Sulphur Diesel (61.0 p/L), electricity (0 p/L), liquid H_2 (0 p/L) listed on the UK DirectGov and Customs Budget (2011); BEV converts 0.14 p/kW h to 1.35 p/litre based on a conversion of 1.0 l UK auto gasoline = 9.67 kW h. Therefore fuel price at the pump is: petrol (1.25 £/L), diesel (1.27 £/L), electricity (1.35 £/L), liquid H_2 (0.35 £/litre); for PHEV a split cost between UK auto gasoline and electricity (1.30 £/litre) is used.

Fuel consumption assumes 45% highway, 55% city driving at 24,000 km/year and accounts for real world driving conditions i.e. faster speeds and acceleration, air conditioner use, colder outside temperatures based on the US Environmental Protection Agency (EPA) [40]. Those values have been compared against the new European drive cycle (NEDC), which does not account for real world driving conditions, which can significantly overestimate fuel economy. The UK government recommends uplifting NEDC data to bring it closer to anticipated real-world vehicle performance [41]. The International Energy Agency uses a factor of +15–18% to convert from test-cycle to real-world values. This reflects values of

Table 1
Vehicle attribute data for UK. *Source*: Refs. [36–38]; US Department of Energy (DOE) Alternative Fuels and Advanced Vehicles Data Centre [40].

Technology	Purchase Price (£)	Running Cost (£/100 km)	Fuel Efficiency (L/100 km)	Acceleration (0–100 km/hr in seconds)	Range (km on 1 tank/charge)	Environment (WTW GHG gCO_2-eq/km)	Refuelling availability (%)
Petrol	10437	10.0	8.1	6.5	567	163	100
Diesel	12659	8.76	6.9	8.7	714	155	100
HEV	16407	5.88	4.7	10	862	140	100
PHEV	25275	3.29	4.5	12	764	109	50
BEV	20569	3.21	2.4	11	117	77	1
FC	62750	1.37	3.9	12	384	73	1

Table 2
Model input values normalized and indexed against petrol.

Technologies	Purchase price	Running cost	Fuel efficiency	Acceleration	Range	Environment	Refuelling availability
Petrol	1	1	1	1	1	1	1
Diesel	1.21	0.88	0.85	1.34	1.26	0.95	1
HEV	1.57	0.59	0.58	1.54	1.52	0.86	1
PHEV	2.42	0.33	0.56	1.85	1.35	0.67	0.50
BEV	1.97	0.32	0.29	1.69	0.21	0.47	0.01
FC	6.00	0.14	0.48	1.85	0.68	0.45	0.01

+15.5% from the Energy Saving Trust (EST) based on information from the UK's biggest fleet operator (ARVAL) on real world performance of its vehicles relative to test cycle data. Consequently, the UK government recommends applying a +15% uplift factor. Using this uplift factor fuel economy for average petrol and diesel cars are 7.8 L/100 km and 6.2 L/100 km respectively [41]. That was compared to real world adjusted values from the EPA, which is similar at 8.1 L/100 km and 6.9 L/100 km respectively (Table 1). The EPA values are therefore used because of comprehensive coverage across different vehicle typologies and similarity to the values recommended by the UK government. Using the uplifted values avoids placing undue importance on the fuel efficiency parameter relative to the other attributes when assessing consumer preferences. So for consistency the fuel economy values reported by the EPA are used for the remaining vehicles to allow for comparison across vehicle typologies. And although EPA values are not based on the NEDC European standard, the relative performance between vehicles will not change from the consumer's perspective since there is consistent use of EPA values. Also note for the PHEV the average combined cycle between all electric and gasoline modes is used. For acceleration values, petrol and diesel are based on vehicle specifications from company websites and DOE (2011); HEV [42]; PHEV and FC [43]; and, BEV estimate is based on company websites. Vehicle range values are based on selected vehicle specifications from DOE (2011).

Refuelling availability is a relative measure of the importance of range anxiety in consumer decision-making. It does not necessarily imply specific numbers of AFV refuelling stations relative to ICEs since this would require normalization against vehicle range. To assess actual numbers of refuelling stations would require neighbourhood level spatial infrastructural data along with vehicle range and trip length as a function of trip journey purpose. This is currently outside the scope of the current study but would be an important issue for further research since the UK is implementing various programmes to support a rollout of charging points for BEVs. In the current study, it is assumed that from a consumer perspective there is no range anxiety associated with ICEs and set refuelling availability at 100%. For PHEVs there are currently mixed messages surrounding charging availability in the UK. A Department for Transport [44] study suggests that home charging utilizing a 240 V/13 A or 16 A connection with a switchable socket and surge protection device would not pose a problem for most UK homes. But a more recent study by the UK Royal Academy of Engineering [45] suggests that current planning policies often limit the number of off-street parking places, and in many rented properties, installing charging sockets could be complicated. A conservative estimate is therefore taken in the reference case for PHEVs assuming 50% of consumers can charge from home. For shorter range BEVs the main issue is on-road refuelling availability. The UK has ambitious targets in place including The London Electric Vehicle Delivery Programme, which anticipates the deployment of 25,000 charging stations by 2015 to support ~100,000 BEVs. The Plugged-In Places programme has made £30 m available to match-fund eight pilot projects to support the Carbon Plan commitment to install up to 8500 charging points. These are highly ambitious targets and a more conservative view of BEV infrastructure rollout is taken in this study. In the UK, FC infrastructure is only in trial phases with far less attention compared to BEVs and PHEVs [46]. Therefore, in the reference case BEV and FC refuelling availability (RA) is assumed to be far less than ICEs and is arbitrarily set at 1% relative to ICEs.

Well-to-wheel (WTW) emissions are based on Well-to-Tank (WTT) which accounts for the energy expended and the associated greenhouse gas (GHG) emitted during the steps to deliver the finished fuel to an on-board vehicle tank; Tank-to-Wheels (TTW) is also included which accounts for the energy expended and associated GHGs emitted by the vehicle/fuel combinations based on Concawe [37]. That data has been used for previous UK scenario analysis of WTW emissions under different grid mix assumptions shown in Table 3 [36]. Table 4 shows the vehicle energy use assumptions used in the WTW analysis. The reference case uses Scenario A that reflects the current UK grid mix (~450 gCO_2/kW h).

To calibrate the model historical UK passenger vehicle data was used shown in Table 5. The scrappage rate of the passenger vehicle stock was calculated using vehicle age distribution data (Fig. 1A) and vehicle licensing statistics showing the initial year of registration and the percentage of vehicles remaining on the road as a function of age (Fig. 1B). For 1999–2008 the arithmetic mean scrappage rate is ~14% per year of the total passenger vehicle stock, which is adjusted down to 13% to better fit the model and is assumed to remain constant over the projection period. Each vehicle technology is scrapped in proportion to its' share of the total vehicle stock (TVM).

The growth of the total vehicle stock (Φ_{TVM}) is set at 1.2% per annum over the projection period. This assumption is based on UK government trend data and macroeconomic forecasts where

Table 3
WTW vehicle emission under different UK grid mix scenarios. *Source*: DfT [36]; Concawe [37].

Technologies	CO_2 emissions WTW gCO_2-eq/km			
Scenarios		A	B	C
Petrol		163	163	163
Diesel		155	155	155
HEV		140	140	140
BEV		77	60	30
PHEV	Electric mode	77	60	30
	Gasoline mode	140	140	140
	Total 50:50 mix	109	100	85
FC_1	H_2 natural gas	73	72	71
FC_2	H_2 grid electrolysis	162	126	63

Notes: Scenario A = 450 gCO_2/kWh (current UK grid mix); Scenario B = 351 gCO_2/kWh, equivalent to a new combined cycle gas turbine (CCGT) plant; Scenario C = 176 gCO_2/kWh, equivalent to a much lower grid mix achieved through high penetrations of renewables, nuclear, and carbon capture and storage (CCS); Electricity transmission and distribution losses to recharging points of 7% are also included; and for H_2 fuel paths: $FC_1 = H_2$ produced from natural gas in a centralized steam methane reformer, with transport to refuelling stations by pipeline. Electricity demand from compression for pipeline transport and for dispensing is included along with upstream emissions in natural gas extraction; $FC_2 = H_2$ produced by centralised electrolysis, with transport to refuelling stations by pipeline. Electricity demand from compression for pipeline transport and dispensing and transmission losses of 4% are included [36]. For PHEV a 50:50 electric-gas mix is used, and $FC_1 = H_2$ from natural gas.

Table 4
Vehicle energy use assumptions. *Source*: DfT [36], Concawe [37].

		Vehicle energy use MJ/100 km	Reference
Petrol		190	Concawe/JRC/EUCAR for gasoline PISI 2010
Diesel		177	Concawe/JRC/EUCAR for diesel DICI with DPF 2010
HEV		163	Concawe/JRC/EUCAR for gasoline Hybrid PISI 2010
BEV		57.6	Equivalent to 16 kW h/100 km. Current figure for vehicles comparable to that used in Concawe/JRC/EUCAR of 20 kW h/100 km, reduced to include regenerative braking and other battery and motor development
PHEV	Electric mode	57.6	As above
	Gasoline mode	163	Concawe/JRC/EUCAR for gasoline hybrid PISI 2010
FC		83.7	Concawe/JRC/EUCAR for H_2 hybrid FCV in 2010

Notes: PISI = Port Injection Spark Ignition, DICI = Direct Injection Compression Ignition, DPF = Particle filter.

demand for passenger car travel measured in passenger-km or vehicle-km increased 20% between 1990 and 2006, and is currently on a growth trajectory of 1% per annum [5]. Demand is influenced primarily by GDP and population, which are forecasted to grow per annum 2.5% and 0.5% respectively towards 2050 [47]. To calibrate each technology per annum growth was set at: petrol (1.4%), diesel (11%), HEV (16%), PHEV (10%), BEV (10%) and FC (5%). Based on empirical data [45], to initialize the model at the year 2000 it is assumed that the remaining 0.1% of the non-incumbent passenger vehicle stock is comprised of HEV (0.07%), PHEV (0.01%), BEV (0.01%) and FC (0.01%).

Fig. 2 shows the model fit against real data using a linear regression giving a reasonable fit (R^2 = 0.9702 at 95% confidence bounds).

Fig. 3 plots real data versus modelled data over the calibration period for individual technologies. At the individual technology level there is much greater fluctuation in the model. This is due

Table 5
UK passenger licensed vehicles by propulsion type from 1999–2008 (in thousands).

Year	Petrol N	Diesel N	Petrol/gas N	Gas[1] N	HEV N	Other[2] N	Total
1999	21,031	2930	13	1	–	–	23,975
2000	21,233	3153	19	1	–	–	24,406
2001	21,641	3460	21	3	1	–	25,126
2002	21,839	3912	23	6	1	–	25,782
2003	21,805	4400	24	10	1	–	26,240
2004	21,977	5011	25	13	3	1	27,028
2005	21,876	5596	26	14	8	1	27,520
2006	21,635	6135	27	16	17	1	27,830
2007	21,432	6716	27	18	32	2	28,228
2008	21,064	7227	27	23	47	2	28,390

Notes: (1) includes gas, gas bi-fuel and gas diesel, (2) includes electric and steam propulsion [48].

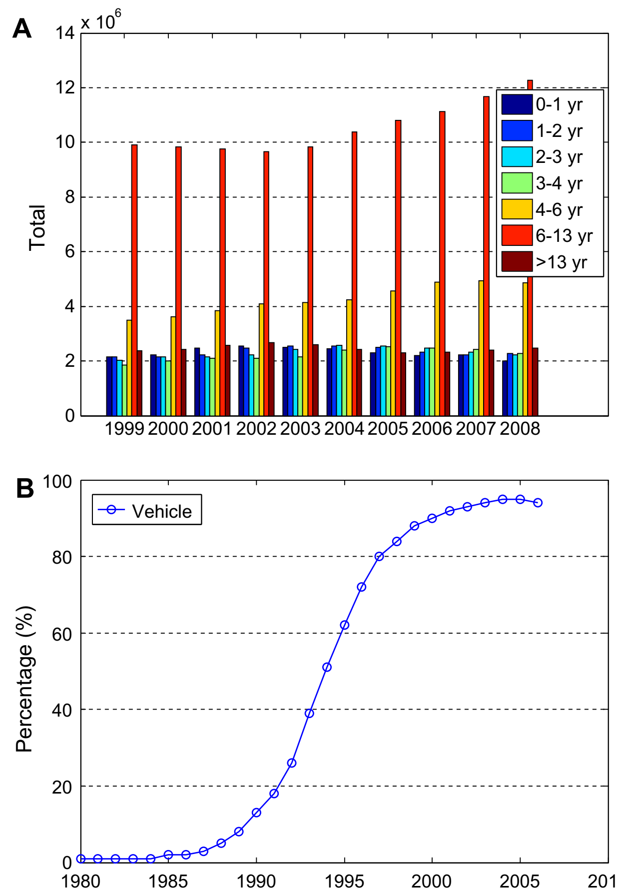

Fig. 1. (A) UK passenger vehicle age distribution 1999–2008 [48]. (B) First registration of passenger vehicles from 1980–2006 and those still licensed at end of 2006 [26].

to the stochasticity introduced into the consumer model coupled with low vehicle stock during the early phases of diffusion. However, the model captures the overall growth trend line for each technology, and by 2008 as each technology is able to cumulatively build up more stock there is greater model convergence with real world data (Fig. 4).

4.2. Scenario development

4.2.1. Reference case

The reference case aims to capture a mass-market consumer profile. In a recent UK consumer survey (web survey *N* = 987; focus

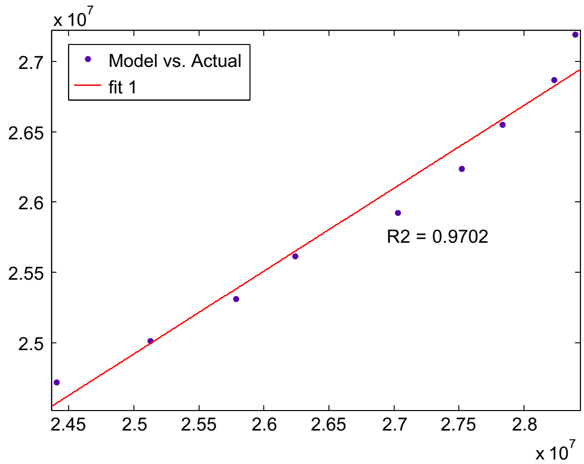

Fig. 2. Model data versus real data for total UK passenger vehicle stock 2000–2008. Real data plotted on *X*-axis, model data plotted on *Y*-axis. Linear regression with 95% confidence bounds on coefficients.

group, $N = 52$) the most important vehicle purchasing factors were reported in the following order of importance: (1) fuel economy/running costs, (2) size/practicality, (3) vehicle price, (4) style/appearance, and (5) reliability. Metrics relating most to environmental performance including vehicle emissions, fuel and vehicle type, and road tax band were less important ranking at 10, 12 and 15 respectively [49]. And for potential adopters of AFVs, consumer surveys from across different global markets indicate that lack of refuelling infrastructure is a major deterrent for adoption [50,51]. Therefore, in the reference case more weight is given to purchase price, fuel consumption and refuelling availability attributes by specifying the consumer preference distributions, $f(\cdot)$ as lognormal while keeping all other attributes distributed standard normal. This implies that consumers are more sensitive to those parameters and are negatively influenced by high purchase price and lack of refuelling availability, but positively influenced by high fuel economy. In subsequent scenarios higher consumer weighting is placed on other attributes to see how that influences adoption behaviour. The reference case probabilities are then passed as a vector into the technology diffusion model, calibrated against UK vehicle stock data 2000–2008 discussed above and then projected to 2035.

4.2.2. Evolving market scenarios - technology and behavioural change

These scenarios aim to see the influence of technological change upon consumer adoption behaviour. The coupled effects of evolving technological attributes and changing consumer preferences on diffusion are assessed. First, technological change upon a mass-market consumer profile (as developed in the reference case) is evaluated, and then the effects on a stylized early adopter market. Past empirical work shows that adoption behaviour is strongly influenced by consumer preferences for specific attributes of a particular technology or innovation. It is expected that AFVs will become more competitive as costs decrease and performance improves [8,52]. However, incumbent technologies will also continue to evolve and improve, which is not often accounted for since most of the focus is generally on rapidly advancing AFVs. But most consumers are risk averse to new unproven technologies. In a competitive market, how quickly competing technologies improve and meet consumer expectations, will influence the likelihood of adoption. While there has been extensive analysis on technology learning rates for ICEs and AFVs where costs decrease with cumulative doubling of stock [8] less is known about how changes in

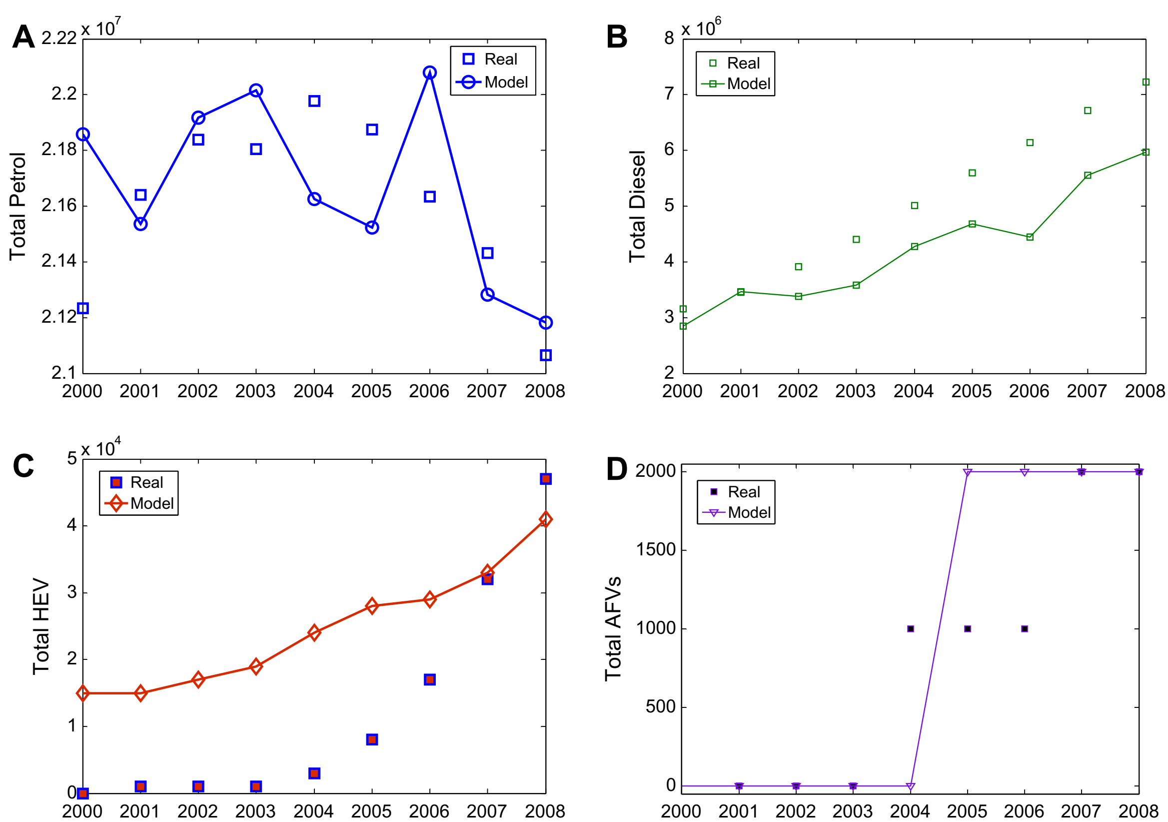

Fig. 3. Comparison of technology model outputs versus real data for each vehicle group in the UK from 2000–2008. AFV real data includes electric and steam propulsion cars. The model does not include steam propulsion but includes PHEV, BEV and FCs.

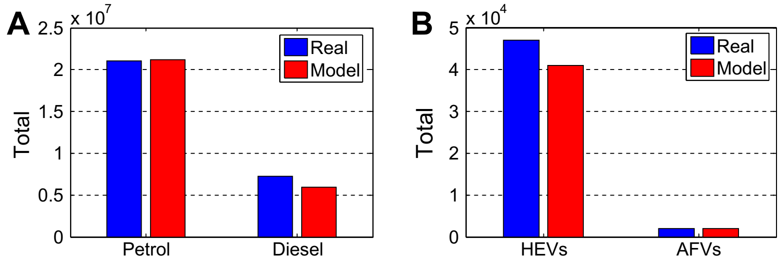

Fig. 4. Model outputs versus UK real data in 2008 for each technology group showing a good match for cumulative stock growth in the reference case for (A) incumbent vehicles, and (B) AFVs.

Table 6
Advanced engine and transmission efficiency savings, and indicative production costs.

Technology	Efficiency (%)	Cost/vehicle (£)
Direct engine and lean burn	10–13	200–400
Variable valve actuation	5–7	175–250
Engine capacity downsize + turbocharging/ supercharging	10–15	150–300
Dual clutch transmission	4–5	400–600
Stop-start	3–4	100–200
Stop-start + regenerative braking	7	350–450
Electric motor assist	7	1000
Reduced mechanical friction components	3–5	Negligible

Notes: Ranges derived from a number of sources, including the International Energy Agency (IEA), Institute of European Environmental Policy (IEEP), California Air Resources Board (CARB), Ricardo. Cost estimates derived using approximate conversion to Sterling reported in Ref. [57].

technological performance will influence adoption behaviour, especially for different adopter groups. Given that consumers are heterogeneous with different preferences there is need to understand how various market segments respond to advancements in incumbent technologies and the related impacts upon the expected uptake of AFVs.

Therefore, scenarios that focus on vehicle efficiency improvements and the related effects upon CO_2 emissions and running costs are developed. Those improvements will arise from industry experience through technology learning, and spill over effects linked to research and development (R&D) [53]. How those technological changes influence the probability of adoption for both mass and early market adopters are assessed. A recent UK study reported that financial gains from improved fuel economy and government policy, along with environmental appeal were key factors for early adoption of HEVs [54]. Similar results have also been found in empirical work across Europe and the US [55]. To simulate an early adopter profile consumer sensitivity to fuel prices and carbon emissions are increased. The sensitivity to purchase price, fuel economy and refuelling availability are also maintained to see relative difference between mass and early market adopters. The assumption here is that characteristics of HEV early adopters may also reflect potential adopters for other AFVs.

4.2.2.1. ICE efficiency assumptions. There are various estimates for the rates of efficiency improvements for current ICE technologies. In the UK, between 1999 and 2008 fuel efficiency for medium size petrol cars improved from 39 to 45 miles per gallon (mpg) [56] and between 1997 and 2007 new passenger vehicle emissions improved from 190 to 167 gCO_2/km implying efficiency improvements of ~1.5% per year [57]. A recent study for the European market suggests that 13% vehicle efficiency improvements could be obtained over the next 8 years [58]. This includes: 3–5% powertrain efficiency increase from new technologies based on the trends of the last decade (despite signs that conventional powertrains are reaching their limits indicated by near zero improvements in diesel vehicle CO_2 emissions between 2006–2010; 0.5–1.5% improvement in average powertrain efficiency from increased diesel share; 1–3% gain from application of electric-assist systems (not hybrid-electric vehicles) such as an idle shut off function; 6–7% gains from improvements in vehicle characteristics such as curb weight, aerodynamics and rolling resistance [58]. More optimistically, the King Review [57] conducted for the UK government suggests 30% vehicle efficiency savings over the next 5–10 years coupled with additional production costs of ~£1000–1500 per vehicle assuming economies of scale are reached (Table 6). Those estimates imply a range of 1.7–2.7% efficiency improvements per year over the period 2015–2020, and using the higher range value of £1500 implies a 1.4% increase per year in vehicle production costs. For this scenario the mean approximation of 2.0% per year efficiency gains for petrols and diesels are used. Corresponding changes to carbon emissions and running costs are made based on a linear relationship between vehicle efficiency and emissions [57,58]. It is assumed that additional production costs are passed on to the consumer increasing the purchase price 1.5% per year (See Table 7 for adjusted parameters).

4.2.2.2. AFV efficiency assumptions. There is greater uncertainty surrounding future improvements in battery technology. However, Li-ion batteries may prove to be the best option for mass

Table 7
Adjusted parameters for mass and early market scenarios relative to reference case.

Scenario	Mass market				Early market			
	1		2		3		4	
	PP	VE/RC/CE	PP	VE/RC/CE	PP	VE/RC/CE	PP	VE/RC/CE
Petrol	1.5	2	1.5	2	1.5	2	1.5	2
Diesel	1.5	2	1.5	2	1.5	2	1.5	2
HEV	0	2	0	4	0	2	0	4
PHEV	0	2	0	4	0	2	0	4
BEV	0	2	0	4	0	2	0	4
FC	0	2	0	4	0	2	0	4

Notes: Values indicate percentage change (%Δ) per year over projection period including an increase in purchase price (PP) and vehicle efficiency (VE) with corresponding decreases in running costs (RC), and carbon emissions (CE) for mass (1, 2) and early (3, 4) market scenarios.

commercialization of AFVs due to advantages in specific energy and power values [59,60]. Between 1990 and 2005, the average annual rate of energy density improvements for Li-ion was 7% reaching 450 Wh/L in 2005. For Li-ion's closest competitors, nickel–metal hydride (Ni-MH) reached 350 Wh/L and nickel–cadmium (Ni-Cd) reached 130 Wh/L representing 4% and 1% improvements respectively over the same period [52]. In terms of future improvements, the DfT [44] assume from 2010 to 2030, BEV efficiency will increase from a current 0.16 kW h/km to 0.11 kW h/km implying ~2.0% per year gains. Increased experience with BEV battery technology will also assist fuel cell development through technology learning-by-doing effects [61]. Li-ion batteries are in the early stages of development with considerable room to improve compared to ICE technologies. In order for AFVs to compete against ICEs, battery technology will have to improve considerably, combined with large decreases in cost. For mass commercialization of PHEVs for instance, it is expected that battery storage will need to increase from 5 kW h to 20 kW h while costs will need to drop from \$1000/kW h to \$300/kW h over the next 10 years [8].

The sensitivity of consumer adoption to improved AFV performance relative to improvements in ICEs is tested. It is first conservatively assumed that AFV efficiency improves at the same pace as ICEs, and then outpaces ICEs by 100%. Corresponding changes to AFV running costs and carbon emissions are made. It is important to note that the simplifying assumption is made that HEVs, PHEVs, BEVs and FCs improve at the same rate, allowing for a more general assessment of competition between advanced ICEs and AFVs from the perspective of early and mass adopters. Looking at historical

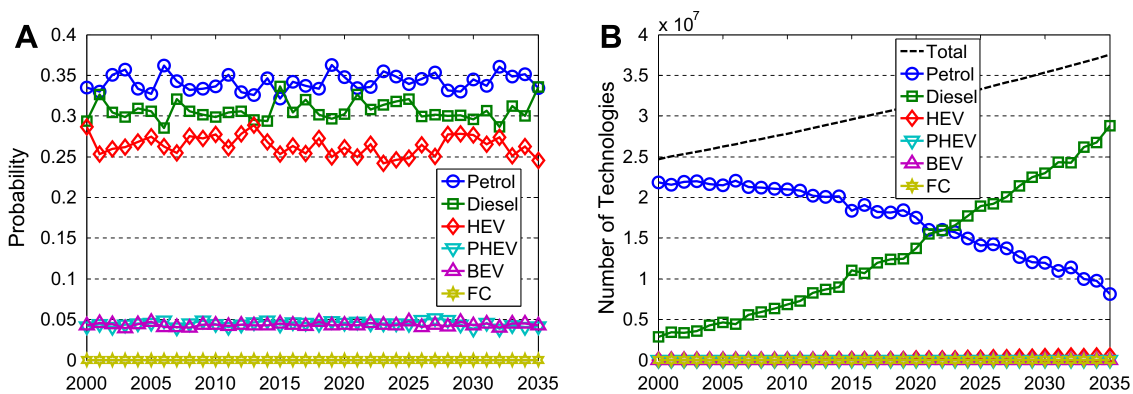

Fig. 5. (A) Reference probabilites and (B) diffusion of vehicle technologies for UK mass market.

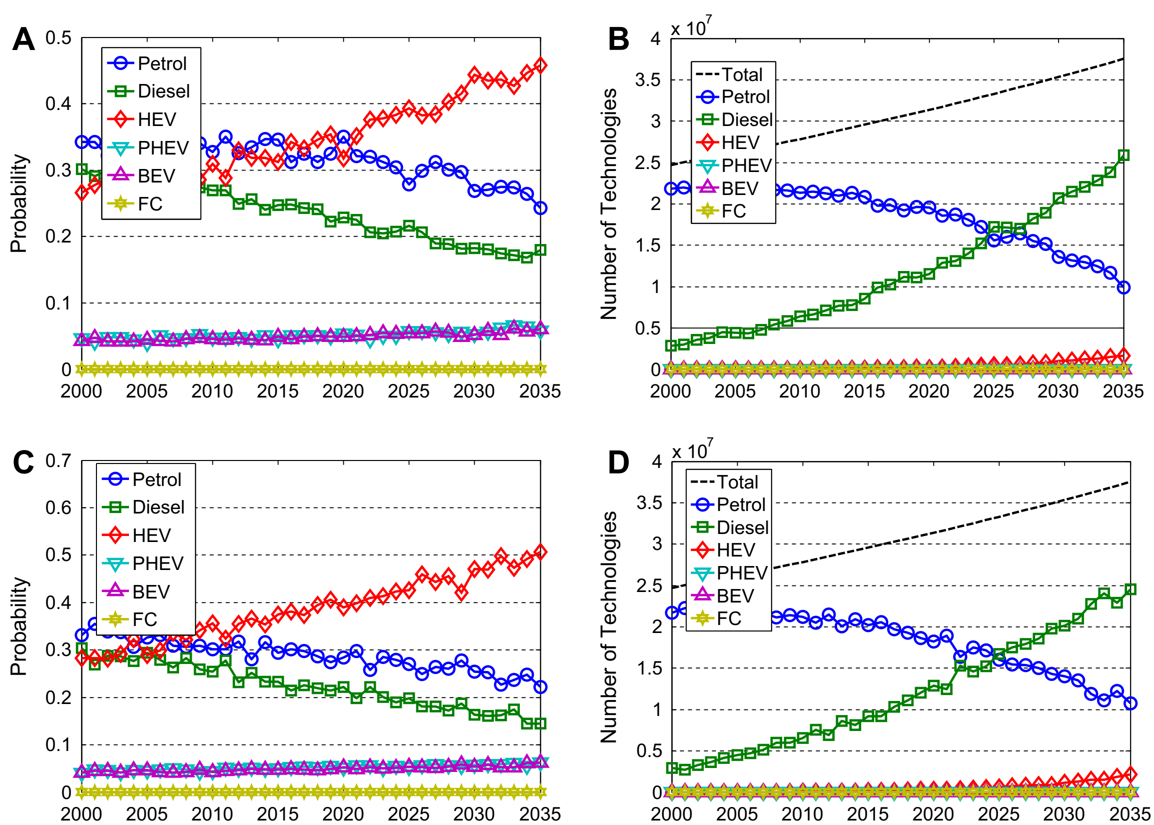

Fig. 6. Mass market scenarios showing coupled technology and behavioural change: (A) consumer probabilities and (B) market diffusion assuming equal efficiency improvements between ICEs and AFVs with increasing ICE purchase prices and AFV prices held constant; (C) consumer probabilities and (D) market diffusion assuming rate of AFV efficiency improvements are twice as fast as ICEs with increasing ICE purchase prices and AFV prices held constant.

trends in battery technology indicates continued decreases in production costs as those technologies improve [52,62]. Trends in ICE efficiency gains have slowed in recent years with less room to improve than in the past [58]. This means that ICE improvements will come at a higher incremental cost than for battery technologies over time [57]. The important unknown is over what time scale the price gap will close allowing battery vehicle technologies to compete with ICEs. Purchase prices for AFVs will have to decrease considerably in the near future to induce adoption. One way to decrease the price gap between ICEs and AFVs is to account for the higher incremental costs for continued ICE advancements, which is not often explored in the literature.

The model therefore accounts for the purchase price change that may arise from different incremental costs related to technological improvements rather than assuming arbitrary decreases in AFV purchase prices. It is assumed that AFVs efficiencies will continue to increase but the costs are not passed onto the consumer either through policy or other interventions such as the $5000 capital incentive recently implemented in the UK [63]. That seems optimistic, but using the higher £1500 value for increased ICE production costs related to efficiency improvements, and not passing the additional costs of AFVs to consumers, those assumptions only imply a 1.5% per annum decrease in the price gap between ICEs and AFVs over the projection period. This is conservative compared to other estimates suggesting AFV capital cost reductions of 7% and 6% per year for BEV and FCs respectively [62], or a 70% decrease in battery storage costs over the next 10 years [8]. The adjusted input parameters for mass and early market scenarios are summarized in Table 7.

5. Results and discussion

5.1. Reference scenario

Fig. 5A shows the consumer probabilities to adopt each technology for the reference case giving: petrol (34%), diesel (31%), HEVs (26%), PHEVs (4%), BEVs (4%), FC (<1%) and Fig. 5B shows the resulting diffusion curves. The simulated probabilities are compared against a recent empirical study in the UK that analyzed mass-market adoption of AFVs based on survey data [64]. The mass market coefficients developed from the survey implied adoption probabilities that were similar to this analysis except that HEVs were higher at ~35%, and PHEVs and BEVs were nearly double at ~8% each. That study however indicated a discrepancy between the survey results and their own modelling work stating that consumer survey valuations for fuel economy were unrealistically high implying the average consumer capitalizing up to 20 years of fuel costs at point of purchase. This over estimation may have resulted from survey ‘expectation bias’ where respondents tend to overestimate the factors they perceive the survey is investigating, or difficulty in converting fuel consumption data into a yearly cost [64]. The simulated probabilities with lower preferences for AFVs may therefore better reflect the current mass market in the UK.

Panel A shows that in the reference case random consumer behaviour is captured shown by fluctuations in probabilities at each time step, but over time reveals a trend in consumer preferences that does not change considerably over the projection period. Based on those preferences, Panel B indicates that the system flips by ~2025, with diesels displacing petrol’s as the dominant technology. This trend is also reflected in the European passenger car market with the rapid uptake of diesels in recent years. The reference case also shows that without immediate and sustained policy intervention combined with aggressive industry investment, AFVs will not be able to compete with incumbent technologies thereby falling short of UK policy goals to decarbonize the transport sector and alleviate oil dependency on foreign reserves. The mass-market reference case was also compared against other business-as-usual scenarios developed for the UK giving similar results [5,65].

5.2. Evolving market scenario results

Mass market and early adopter results are shown in Figs. 6 and 7 respectively. The simulations consistently show that if AFVs can keep pace or exceed ICE improvements this will positively influence their diffusion. And even if ICEs continue to improve performance, they will face increasing competition from HEVs, albeit in small volumes when looking at cumulative build up in vehicle stock. These results reflect recent empirical trends in the UK for HEV adoption. From 1999 to 2008, UK average per annum percentage increases in new vehicle registrations were: petrol ~1%, diesel ~10%, HEV ~50%, and all other advanced technologies < 8% [48]. The noticeable change in recent years has been increased adoption of HEVs, which is reflected in our results showing a relatively high probability of adoption and accelerated diffusion. However, the results also show that even if preferences for HEVs take off and surpass ICEs, it will take a considerable amount of time to achieve sizeable market penetration. This is because HEVs begin from such a small fraction of the total vehicle stock. This is important to note given the highly optimistic expectations for rapid diffusion of other currently less competitive AFVs that have even a smaller base from which to grow from. This suggests the large amount of inertia in the UK technological system that has to be overcome to achieve even small penetrations of AFVs, even under optimistic assumptions that reflect less risk averse early adopters.

Table 8 shows the cumulative build up of each technology for all scenarios by 2035. Across the simulations it is shown that efficiency improvement in AFV technologies and the associated benefits of reduced running costs and CO_2 emissions have a positive effect on cumulative adoption in mass and early markets. This is particularly true when AFV improvements outpace ICEs leading to more than a doubling in cumulative adoption relative to when all technologies improve at the same rate. HEVs are able to take market share away from petrols and diesels most notably in the early adopter market increasing > 5 times relative to the reference case. This occurs despite increasing efficiency gains for petrols and diesels since those benefits are partially offset by rising production costs that are passed on to the consumer.

However, in the mass market, petrols also benefit from efficiency improvements despite increasing purchase prices shown by higher cumulative growth relative to the reference case. It is only in the early market that petrol’s cumulative growth is stabilized due to higher penetrations of AFVs. This is because most of the market share is taken away from diesels rather than highly competitive petrols. This has negative implications for phasing out the incumbent system dominated by petrols and relying on increasing fleet wide efficiency gains from increased diesel uptake. Even when it is assumed that consumers gain the benefits of AFV technology improvements without the associated costs, BEV and PHEV only make up a small fraction of the total vehicle stock. This implies that although different incremental costs between ICEs and AFVs related to technology improvements will accelerate AFV diffusion additional measures will have to be taken to further decrease the price gap. These results also show that even if AFVs improve more rapidly than ICE’s it will be difficult to surpass petrols since they also benefit from technological improvements.

6. Conclusions and further research

This study has focused on technological improvements for advanced ICEs and how that might affect the diffusion of AFVs. This has not been well explored from the perspective of influencing

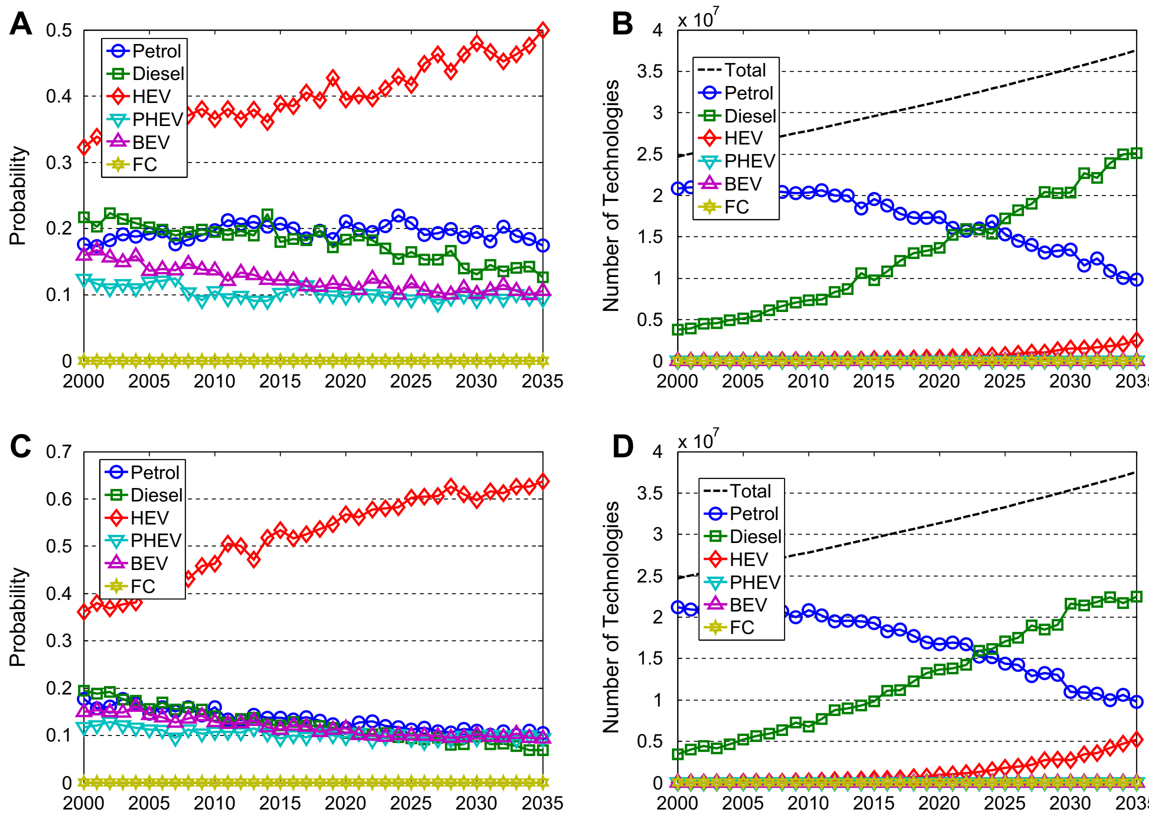

Fig. 7. Early market scenarios showing coupled technology and behavioural change: (A) consumer probabilities, and (B) market diffusion assuming equal efficiency improvements between ICEs and AFVs with increasing ICE purchase prices and AFV prices held constant (C) consumer probabilities and (D) market diffusion assuming rate of AFVs efficiency improvements are twice as fast as ICEs with increasing ICE purchase prices and AFV prices held constant.

consumer adoption in mass and early markets. This paper differentiated the market into mass and early adopter profiles based on UK empirical surveys to assess how consumers with different preferences might respond to changes in technological performance. Results show that if AFVs can keep pace and exceed ICE efficiency gains, this will positively influence adoption despite increasing competition from advanced ICEs on parameters that currently favour AFVs such as high fuel economy and environmental performance. However much of the gains are made at the expense of diesels rather than petrols that also benefit from improved performance. Additionally, increased adoption of AFVs also depends on decreasing the price gap between ICEs and AFVs. Although cumulative adoption will increase with improved AFV performance, it will only occur in small volumes over the projection period with the possible exception of HEVs. This suggests there is considerable inertia in the current UK vehicle system. It is expected that industry will need to heavily invest to make more AFV vehicle models available to meet different consumer markets. By 2020, the IEA [66] forecast that up to 40 models of PHEVs and 20 models of BEVs would need to be developed to achieve large-scale adoption. This coincides with total new or replacement models to be offered by manufacturers worldwide over the same period. Those supply-driven forecasts assume aggressive manufacturer investment and government policy support for AFVs. This analysis suggests that even if massive industry investment into AFVs occurs increasing their market exposure and availability, they will not be adopted en masse unless they are able to meet specific consumer preferences at the attribute level. For example, these results imply that industry and government will have to ensure that the rate of AFV improvements at least keep pace with ICEs, but more likely will have to far exceed ICEs to induce adoption. Moreover, those advancements will have to occur

Table 8
Cumulative diffusion of technologies across scenarios in 2035.

Scenario	Reference	Mass market		Early market	
		1	2	3	4
Petrol	9.8 m	9.9 m	11 m	9.8 m	9.7 m
Diesel	27 m	26 m	25 m	25 m	22 m
HEV	675 k	1.7 m	2.2 m	2.5 m	5.2 m
PHEV	2 k	5 k	6 k	11 k	17 k
BEV	2 k	5 k	6 k	12 k	17 k
FC	<1 k	<1 k	<1 k	<1 k	<1 k

Note: Scenario 1–4 see input assumptions in Table 7.

while keeping incremental costs down, where industry and government will have to ensure that rising costs are not passed onto the consumer. Otherwise consumers will continue to select highly competitive petrols that also benefit from improved performance and lower costs further attracting low-risk consumers that are already comfortable with that technology.

Although this work shows the influence of changing consumer behaviour and evolving technological attributes on adoption, further work needs to be done on supply-side investment dynamics. For instance, the above scenarios did not change the growth parameters used in the reference case, which could be done in future analyses to simulate additional supply-side investment from industry. That could be coupled with technology learning rates for each technology showing a feedback effect, where increasing industry investment would influence technological performance and adoption. One could then evaluate the positive feedback effect that accelerated adoption would have on decreasing purchase prices as a function of cumulative stock growth. Future work will look more closely at those supply-side effects including increased supply investment targeting specific consumer groups, and how consumers may respond to greater availability of vehicles on market.

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