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# Simulating early adoption of alternative fuel vehicles for sustainability

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ABSTRACT

We quantify the conditions that might trigger wide spread adoption of alternative fuel vehicles (AFVs) to support energy policy. Empirical review shows that early adopters are heterogeneous motivated by financial benefits, environmental appeal, new technology, and vehicle reliability. A probabilistic Monte Carlo simulation model is used to assess consumer heterogeneity for early and mass market adopters. For early adopters full battery electric vehicles (BEVs) are competitive but unable to surpass diesels or hybrids due to purchase price premium and lack of charging availability. For mass adoption, simulations indicate that if the purchase price premium of a BEV closes to within 20% of an in-class internal combustion engine (ICE) vehicle, combined with a 60% increase in refuelling availability relative to the incumbent system, BEVs become competitive. But this depends on a mass market that values the fuel economy and $CO_2$ reduction benefits associated with BEVs. We also find that the largest influence on early adoption is financial benefit rather than pro-environmental behaviour suggesting that AFVs should be marketed by appealing to economic benefits combined with pro-environmental behaviour to motivate adoption. Monte Carlo simulations combined with scenarios can give insight into diffusion dynamics for other energy demand-side technologies.



## 1. Introduction

Achieving sustainable energy policy requires rapid diffusion of new technologies i.e. smart grids, electric vehicles, photovoltaic, heat pumps, smart meters, etc. [1,2]. But it is not well understood whether consumer adoption patterns will support large-scale diffusion. One of the most difficult sectors to decouple from unsustainable fossil fuel use is transport. Globally, the transport sector's total final energy consumption is ~27% with a similar outlook towards 2035 [3]. Consumer acceptance of alternative fuelled vehicles (AFVs) such as hybrid electric (HEVs), plug-in hybrid electric (PHEVs), full battery electric (BEVs) and hydrogen fuel cell (FCs) vehicles is expected to play a major role in decoupling transport's ~93% dependence on liquid fossil fuels [1]. Yet a major area of uncertainty for energy policy is how to overcome consumer risk aversion and accelerate adoption of AFVs across global markets. Our ability to identify potential markets and incentivise early adoption will depend on understanding consumer heterogeneity including different preferences, lifestyles and other motivating factors that may influence adoption behaviour.

For AFVs little is known about the combination of factors that might shift a mass-market adopter into an early adopter category. The aims of this paper are to 1) synthesise and assess recent findings of early adoption behaviour, and 2) develop a

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Monte Carlo simulation model which is able to assess different combinations of technological and behavioural factors that might trigger large-scale adoption. This paper takes a novel approach by combining Monte Carlo simulations with scenario analysis, which could be used to assess a wide range of consumer behaviour for commercializing new energy technologies. The paper proceeds as follows: empirical review of global AFV markets, methods and data, simulation results and discussion and, limitations of analysis and further research.

## 2. Empirical review

### 2.1. Alternative fuel market

To gauge the potential EU market for BEVs, a recent industry on-line survey (N = 4760) covering Belgium, France, Germany, Italy, Spain, Turkey and UK was conducted [4]. Country level data was normalized by total adult population for each country to represent a pan-European demographic sample adjusting for differences in sample size at country level (overall margin of error for pan-European results were reported at 1.4%). The survey indicates that 16% of respondents were *potential first movers* most likely to buy or lease a BEV, 53% *might be willing to consider* meaning they are interested but less likely to purchase, and 31% were *not likely adopters* of BEVs. The survey further suggests that 1–2% of the potential first movers will be *early adopters*. When comparing the stated interest in AFVs against actual sales there is geographic variation. In 2009/10, global sales of HEVs, BEVs and PHEVs reached ~934,000 units representing 2.0% of the world's 45 million passenger vehicles [5]. In 2009, US sales of HEVs and PHEVs reached ~270,000 units, or 2.8% of total passenger vehicles sales [6]. The US accounted for nearly 40% of the global HEV market [6]. In the same year, European HEV sales were markedly lower at ~73,500 units, or 0.4% of total passenger vehicle sales [7]. This is primarily because of a more established EU diesel market that offers competitive fuel economy with petrol-HEVs but at a comparatively lower purchase price. Another reason is that consumer choices remain limited with around 8 HEV models available and only 3 in the non-luxury class. In the US, there were 8 HEV, 5 BEV, and 2 PHEV models available that year [5,6].

In 2009, China became the largest automotive market in the world reaching 13.6 million total vehicle sales, surpassing the 10.4 million sold in the US. Although, HEVs have been available in China since 2005, only ~1900 were sold in 2009, less than 0.1% of the passenger vehicle market [5,6]. This is likely due to the highest price differentials where the cost of an imported Japanese HEV is more than twice the cost of a domestic ICE. Conversely, the largest AFV market in the world is in Japan where combined sales of HEVs and PHEVs reached ~350,000 in 2009, or 10% of total passenger vehicle sales [5]. Fig. 1 compares the difference between total passenger vehicle market versus HEV and BEV sales by region showing the US and Japan commanding 89% of sales despite

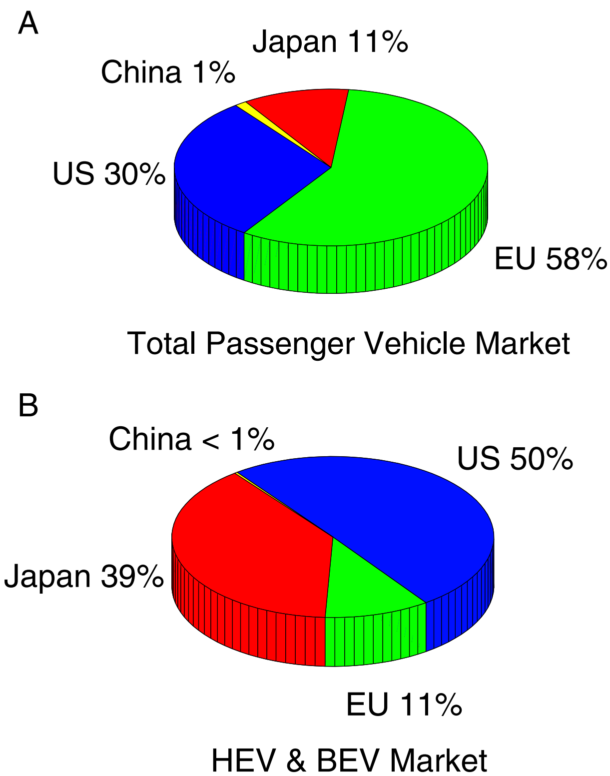


**Fig. 1.** A) Total passenger vehicle market, B) HEV and BEV sales by region in 2009. Calculated from data in refs [5–7].

the EU having nearly 60% of the total passenger vehicle market. What is also shown is that despite China having the single largest automotive market in the world, its passenger vehicle fleet is a fraction of the total at 1%. This is expected to rapidly change as Chinese purchasing power increases over the next few decades [6].

### 2.2. Early adopter profile

Across global markets we are beginning to acquire more information on the characteristics of HEV early adopters. This may give us better understanding of consumer purchasing motivations to accelerate diffusion of AFVs along with other new energy technologies. For the EU and US, recent industry surveys suggest that early adopters of BEVs will be generally male, between 18 and 34 years of age, educated, have a high household income (HHI), already own a vehicle, are environmentally aware, interested in new technologies and sensitive to government incentives and knowledgeable about fuel economy [8–10]. Early majority consumers are individuals most likely to buy immediately after early adopters. These consumers also have a higher than average HHI (~$114,000) between the age of 40 and 44, and are also politically active and environmentally motivated [9]. The expectation is that potential adopters of PHEVs, BEVs and eventually FCs may resemble the consumer profile of HEV buyers.

To compare, a recent UK academic study of HEV adopters (N = 1263) report 74% were male, 42% were > 65 years of age, 52% were a retired couple or single, 39% have a HHI > £48,000 net per year (~$78,000 USD, 2011), and 58% have an extra car [11]. Interestingly, the study suggests that the typical HEV adopter was not significantly distinct from other consumers except that they were better informed about the financial benefits associated with HEVs such as improved fuel economy or different government incentives. The relatively minor differences between adopter categories is also reflected in EU industry surveys about BEVs, which reported that the only major difference between *potential first movers* and the *might be willing to consider* group is that the latter are far less informed about BEVs with only 8% stating that they felt very knowledgeable about the technology [10]. The important question is if there are only minor differences between potential adopter categories for AFVs what would it take to incentivise an individual to move from a late adopter into an early adopter group?

### 2.3. Purchasing motivations

We now have some empirical evidence of the purchasing motivations of HEV early adopters which may inform commercialization strategies for other AFVs. These include: financial benefits i.e. improved fuel efficiency or policy-related advantages such as access to car pool lanes; environmental concern and the symbolic image conveyed by driving a hybrid; compliance with the social norms of a group where hybrid adopters tended to be geographically clustered forming communities [11]. This can create an ideology or perception that hybrid car ownership reflects a particular community's values and norms [12]. Other empirical studies show that new technology was considered intrinsically attractive to HEV adopters [13]. These consumers have positive attitudes to innovations and are likely to adopt new technologies [14]. Another group of HEV adopters were motivated by achieving oil independence through reduced petrol consumption [11,14].

In a recent industry survey [5], reliability is a common purchasing motivation between HEV adopters and all other buyers. However, factors that most influenced non-HEV adopters were notably different. Some of the largest differences are: > 63% of all buyers cite purchase price as one of the most important factors for adoption compared with 39% of HEV buyers; ~52% of all buyers cite vehicle styling as an important purchasing factor versus 31% for HEV buyers; and only 40% of all buyers cite fuel economy as one of the most important factors for adoption, far less than 81% for HEV buyers [5].

## 3. Methods and data

One way to model consumer behaviour is to characterise individual decision-making based on agent preferences for technology attributes. Choice modelling has been widely used to assess consumer behaviour and is able to simulate mass and niche market behaviour [15–17]. We use a highly flexible choice model based on Monte Carlo simulations, which relies on probability distributions to capture consumer behaviour [18,19] , where adoption is based on the probability, $P_{ijn}$ that agent $i$ will select technology $j$ in year $n$ given a finite set of options on market. The model captures heterogeneity in consumer sensitivity to technological attributes specified as the utility of person $i$ from adopting technology $j$ is

$$U_{ij} = b_i X_{ij} + e_{ij} \tag{1}$$

where $X_{ij}$ are observed vehicle attributes including purchase price, fuel price, fuel consumption, acceleration, range, $CO_2$ emissions, and refuelling infrastructure (Table 1). $\beta_i$ is a vector of random coefficients representing consumer preferences for vehicle attributes and $\varepsilon_{ij}$ is a random error term that is independently and identically distributed (iid) across alternatives specifically a type I extreme value error term. If the vector of $\beta_i$'s are based on observations, then $P_{ijn}$ collapses to the standard multinomial logit (MNL) function since $\varepsilon_{ji}$ is integrated out:

$$P_{ijn} = e^{\beta' * Xij} / \sum_{J=1}^{J} e^{\beta' * Xij} \tag{2}$$

While the MNL has been the industry standard for many years it has constraints such as unrealistically predicting that a change in the attributes of one alternative changes the probabilities of the other alternatives proportionately. Also, the MNL relies

**Table 1**
Vehicle technology attributes.

| Technologies | Purchase price (USD) | Fuel price (USD/160 km) | Fuel consumption (L/100 km) | Performance (acceleration 0–100 km/h in seconds) | Range (km on 1 tank/charge) | Environment (annual WTW GHG $CO_2$-eq emission, metric tonnes) | Refuelling availability (%) |
|---|---|---|---|---|---|---|---|
| Petrol | 16,640 | 12.9 | 8.1 | 6.5 | 567 | 5.9 | 100 |
| Diesel | 20,180 | 11.5 | 6.9 | 8.7 | 714 | 5.7 | 100 |
| HEV | 26,155 | 8.45 | 4.7 | 10 | 862 | 3.9 | 100 |
| PHEV | 40,280 | 7.63 | 4.5 | 12 | 764 | 4.0 | 30 |
| BEV | 32,780 | 3.74 | 2.4 | 11 | 117 | 3.6 | 1 |
| FC | 100,000 | 5.00 | 3.9 | 12 | 384 | 3.2 | 1 |

Data from refs [22,23] unless otherwise stated.
Data notes:

- Vehicle assumptions and specifications: 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 kWh, Li-ion, motor: 111 kW, 3-Phase asynchronous, continuously variable transmission (CVT); BEV: 2011 Nissan Leaf, battery: 360 V, 24 kWh, 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 price is manufacturer suggested retail price (MSRP) in 2011 U.S. dollars (USD) see http://www.motortrend.com/index.html; FC purchase price based on refs [3,24].
- Fuel costs and consumption: petrol, diesel, HEV based on 45% highway, 55% city driving, 24,000 km/year, fuel price of $0.972 per litre. PHEV Fuel cost based on 24,000 km annual driving, electricity cost of $0.11/kWh, gasoline price of $3.90 per gallon; Range and refuelling cost for gasoline assumes 90% of fuel in tank used before refuelling, US Environmental Protection Agency (EPA) fuel economy based on Miles per Gallon of Gasoline Equivalent (MPGe) 1 gallon of gasoline = 33.7 kWh; PHEV fuel economy uses average combined cycle between all electric mode and premium gasoline; BEV fuel cost based on 24,000 km annual driving, electricity cost of $0.11/kWh; EPA Fuel economy MPGe, 1 gallon of gasoline = 33.7 kWh; FC fuel cost based on (miles/kg), 1 kg of $H_2 \cong 1$ gallon of gasoline, ~60 mpg, $3/gallon in 2009 (untaxed fuelling cost at station see http://www.afdc.energy.gov/afdc/pdfs/42284.pdf), 24,000 km annual driving. Fuel economy based on EPA L/100 km (conversions MPG = L/100 km, US liquid gallon). From 2008 EPA has changed methodology estimating MPG accounting for faster speeds and acceleration, air conditioner use, colder outside temperatures.
- Acceleration: petrol and diesel based on vehicle specifications from company websites and ref [23]; HEV [25], PHEV, FC [26], BEV [27].
- Range: based on selected vehicle specifications from refs [22,23].
- Well-to-wheel (WTW) emissions: WTW based on annual greenhouse gas emissions (GHG) in carbon dioxide equivalents ($CO_2$-eq) from full fuel-cycle estimates including the three major GHGs emitted by motor vehicles: carbon dioxide ($CO_2$), nitrous oxide ($N_2O$), and methane ($CH_4$). Full fuel-cycle estimates consider all steps in use of fuel, from production and refining to distribution and final use. Vehicle manufacture is excluded. Based on U.S. DOE, GREET Model 1.8, Argonne National Laboratory. For all sources and assumptions on electricity generation mix for BEVs and PHEVs see ref [22]. Fuel cell WTW emissions are ~50–60% reduction relative to petrol based on gaseous $H_2$ produced from natural gas via steam methane reforming in a centralized plant, see ref [28].
- Refuelling availability is a relative measure of the importance of range anxiety in consumer decision-making. It does not necessarily imply specific numbers of refuelling stations. We assume ICEs have 100% access to refuelling opportunity i.e. no range anxiety associated with incumbent technology. A recent industry survey [9] across the US indicates 81% of respondents prefer to charge from home, but 61% are not currently equipped for home charging i.e. access to garage with electrical outlet. This implies that 39% of respondents do have access to home charging facilities. We take a conservative estimate in the reference case for PHEVs and assume 30% of consumers would be able to charge from home. Because of the shorter BEV range the main constraint is on-road refuelling availability. The U.S. DOE indicate BEV charging stations are in the ~1000 s and even less for FC charging stations with the greatest concentrations of ~500 for both in California. In the reference case we assume BEV, FC refuelling availability (RA) << ICE RA and arbitrarily set BEV and FC, RA = 1% relative to ICEs. This metric suggests the relative level at which range anxiety needs to be mitigated by increased refuelling opportunity for different AFVs.

on highly detailed empirical survey data such as stated preference techniques, which can be costly and time intensive to obtain. Additionally, we know from empirical work that there is often an inconsistency between what consumer's say they prefer and what they are actually willing to pay for. With increasing computational power simulation techniques have since been developed to overcome those constraints [18,19]. For instance, if we do not empirically observe $\beta_i$ we can represent consumer preferences as a probability density $f(\beta|\theta)$ where we specify the functional form $f(\cdot)$ and estimate parameters theta, $\theta$ such as the mean, $\mu$, and standard deviation, $\sigma$. $P_{ijn}$ therefore takes the form of an open integral,

$$P_{ijn} = \int L_{ijn}(\beta) f(\beta|\theta) d\beta \tag{3}$$

In the past such a function was intractable but can now be numerically integrated by Monte Carlo simulations using the following algorithm [19]: Take a random draw, $R$, of $\beta$'s from a density $f(\beta|\theta)$ such that,

$$(\beta_n) \sim f(\beta_n|\theta) \tag{4}$$

Calculate the conditional probability

$$L_{ijn} = e^{\beta' * Xij} / \sum_{J=1}^{J} e^{\beta' * Xij} \tag{5}$$

Repeat $R$ times such that,

$$P_{ijn} = \frac{1}{R} * \sum_{r=1}^{R} L_{ij}(\beta^r) \tag{6}$$

where $R$ is averaged at each time step $n$. The simulated probability $P_{ijn}$ sums to one over the alternatives, which is useful for forecasting market share [15,19]. We can also combine Monte Carlo simulations with scenario analysis widely used in energy systems modelling [1,3,7]. Internally consistent scenario assumptions allow specification of preferential behaviour for different technology attributes thereby simulating consumer heterogeneity. And while these are only exploratory simulations the advantage of this approach is that it allows us to quantify the relative changes in technological attributes and consumer preferences that might trigger widespread adoption. We can therefore modify our assumptions of future market conditions and assess the underlying technological and behavioural dynamics that could lead to large-scale diffusion. Additionally, the combined method of Monte Carlo simulations with scenario analysis could be widely applied to the whole class of demand-side technologies, where diffusion is highly dependent upon consumer preferences and end-use.

### 3.1. Reference scenario

While several density functions can be used for $f(\cdot)$, the normal and lognormal distributions are the most common [20,21]. A lognormal distribution is used if from a theoretical perspective, a beta ($\beta$) coefficient has to take the same sign (+/−) for every individual. This is useful for our analysis because it allows us to assume global preferential behaviour for specific vehicle attributes under different scenario assumptions. For instance, purchase price and lack of refuelling infrastructure are major deterrents for adoption of AFVs [8–10]. The reference case therefore assumes people are negatively affected by purchase price and positively affected by vehicle reliability which we proxy as refuelling availability. We therefore specify $f(\cdot)$ as lognormal for purchase price and refuelling availability, making consumer adoption sensitive to high purchase price and lack of refuelling infrastructure. Normal distributions are used for all other attributes in the reference case. In subsequent scenarios we vary these distributions to give preferential weighting for other attributes and assess adoption. For normal distributions, theta ($\theta$) has a mean value near zero; for lognormal distributions theta is near 1.4, and both distributions have a standard deviation of one. All vehicle attributes, $X_{ij}$ are normalized and indexed against petrol vehicles to assess the relative performance of alternatives against the incumbent petrol based system (Table 2). Refuelling availability is set at 100% for petrol, diesel and HEVs, 30% for PHEVs and 1% for BEVs and FCs. See Table 1 notes for refuelling infrastructure assumptions and Section 4 for sensitivity analysis on refuelling availability. 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). See Table 1 notes for all data sources and assumptions.

### 3.2. Early adopter scenarios

Consumer heterogeneity is simulated by changing the distributions of $f(\beta|\theta)$ under different scenario assumptions. We use the empirical review of HEV early adopters to inform early adopter scenarios. The decision-making criteria and consumer characteristics of HEV adopters are mapped onto the other AFVs to see the effect on adoption relative to ICE's. We assume that characteristics of hybrid early adopters may give us insight into adoption behaviour for other AFVs. To assess the potential for early adoption we give preferential weighting to attributes that HEV adopters specified as having a favourable influence on adoption including lower fuel prices, better fuel economy and lower carbon emissions. This is done by drawing a, $\beta$ coefficient from a lognormal distribution for each of those attributes, $X_i$, simulating global preferential behaviour for those attributes. The negative effects of purchase price and refuelling availability are maintained in order to compare early adopters against the reference case. We further introduce heterogeneity by including income effects [15,19]. This is done by dividing the purchase price attribute by the different average incomes for petrol (\$64,721), diesel (\$85,192) and HEV (\$82,371) adopters [5]. The average HEV adopter income is applied to all other AFVs. This decreases consumer sensitivity to the relatively higher purchase price for AFVs consistent with survey findings that HEV adopters have higher average incomes than petrol buyers. The assumption is that higher average income HEV adopters might reflect a subpopulation that are also more willing to adopt other AFVs as they become increasingly available on market.

### 3.3. Mass adopter scenarios

After the early adopter scenarios we remove the income effects to simulate a single mass market and specify preferential behaviour for all remaining attributes i.e. vehicle acceleration and range. These are meant to be a proxy for overall performance

**Table 2**
Model inputs. All values normalized and indexed against Petrol.

| Technologies | Purchase price | Fuel price | Fuel consumption | Performance | Range | Environment | Refuelling availability |
|---|---|---|---|---|---|---|---|
| Petrol | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Diesel | 1.21 | 0.90 | 0.85 | 1.34 | 1.26 | 0.97 | 1 |
| HEV | 1.57 | 0.66 | 0.58 | 1.54 | 1.52 | 0.66 | 1 |
| PHEV | 2.42 | 0.59 | 0.56 | 1.85 | 1.35 | 0.68 | 0.3 |
| BEV | 1.97 | 0.29 | 0.29 | 1.69 | 0.21 | 0.61 | 0.01 |
| FC | 6.00 | 0.39 | 0.48 | 1.85 | 0.68 | 0.54 | 0.01 |

and reliability, factors that positively influenced ICE adopters. These scenarios are meant to level the playing field between all technologies to assess how competitive they are from the consumer's perspective based on current technological performance. These scenarios make the important assumption that most consumers remain positively influenced by attributes that would typically favour AFVs and weigh those features against typical advantages of ICE's including lower purchase price, refuelling availability, performance and reliability. Consumer studies show that high purchase price and lack of refuelling infrastructure were key deterrents for potential adopters of AFVs [10]. We can expect that capital costs will decrease in the future as learning curves improve for AFVs and economies of scale are reached to some degree. From 1990 to 2005, the average annual rate of energy density (Wh $l^{-1}$) improvements for Lithium-ion batteries (Li-ion) was ~7% with costs projected from a current \$1000 $kWh^{-1}$ to as low as \$300 $kWh^{-1}$ over the next 10 years [3]. Governments around the world are also now deploying refuelling infrastructure to support the uptake of AFVs [6]. The scale and timing of costs decreasing and large-scale deployment of refuelling is far from certain. It is not well understood how variations in those factors will affect adoption behaviour over time. We therefore test the sensitivity of those parameters on AFV adoption (Table 3).

We first run a series of simulations with all attributes preferentially weighted but increase the level of refuelling availability relative to ICEs that we assume to be 100% i.e. there is no range anxiety associated with incumbent technologies. We also remove the preferential weighting for vehicle range under the optimistic assumption that most consumers will not be as sensitive to vehicle range once refuelling infrastructure becomes increasingly available. For instance, most daily vehicle trips are <100 km [7]. A large share of daily driving could be satisfied by a current PHEV all electric range (AER) of 30–40 km. In Europe, 50% of daily passenger car trips are <10 km and 80% are <25 km. In the US, 60% of daily car trips are <50 km and 85% are <100 km [7,23]. Moreover with increasing levels of urbanization it is plausible that the number of shorter trips (<100 km) will continue to increase as a fraction of total vehicle trips taken [24]. In the first round of simulations we increase the level of infrastructure availability for PHEVs, BEVs and FCs relative to ICEs by 30% to 70%. We then couple increasing levels of refuelling availability from 10% to 60% with a decrease in purchase price relative to petrol to see the combined effect on adoption behaviour (Table 3). When taking all factors into account, the objective is to determine what combination of consumer preferences combined with changes in purchase price and refuelling availability might trigger large-scale adoption of AFVs.

## 4. Results and discussion

### *4.1. Reference case*

The reference case captures random fluctuations in adoption behaviour over the projection period (Fig. 2A), but shows a clear trend of ICEs dominating the market (~97%) unless current consumer preferences change dramatically in the future. Mean probabilities (Fig. 2B) over the forecasted period 2000–2030 are petrol (46%), diesel (33%), HEV (18%), PHEV (1.4%), BEV (2%), FC (<<1%).

The combination of petrol attributes is the most attractive for consumers including high performance and reliability coupled with low capital costs. Although petrol has the highest fuel costs, consumers tend to heavily discount (~18–30%) future cost savings while expecting 2–3 year payback periods [25,26]. In the US, consumers typically account for only 3 years of fuel savings which understates the true value of a 14-year vehicle lifespan by ~60% ref [25]. The fuel economy and carbon emission benefits of AFVs are not equally factored in by risk adverse consumers that are familiar and comfortable with the incumbent technology system. Nevertheless, the reference case also shows that despite the current advantage that ICEs have over AFVs, ~2% of the population still adopt BEVs and PHEVs. This infers a sub-population that is less risk averse and willing to test new unproven technologies. This is consistent with empirical findings and consumer surveys that show that there are a small minority of technological innovators or enthusiasts that are willing to adopt AFVs [5,10]. We now explore the conditions that may induce large-scale shift from a reference case mass market to early adoption.

### *4.2. Early adopters*

We simulate a sub-population of early adopters by first introducing income heterogeneity (S1) and then preferential weighting for lower fuel price (S2), fuel consumption (S3), and $CO_2$ emissions (S4) consistent with our empirical review of factors

**Table 3**
Adjusted parameters for refuelling infrastructure and purchase price simulations.

| Simulations | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Refuelling availability | 30% | 40% | 50% | 60% |
| Purchase price relative to petrol | | | | |
| Petrol | 1 | 1 | 1 | 1 |
| Diesel | 1.1 | 1.1 | 1.1 | 1.1 |
| HEV | 1.1 | 1.1 | 1.1 | 1.1 |
| PHEV | 2.0 | 1.5 | 1.3 | 1.3 |
| BEV | 1.5 | 1.3 | 1.2 | 1.2 |
| FC | 3 | 2.5 | 2.0 | 2.0 |

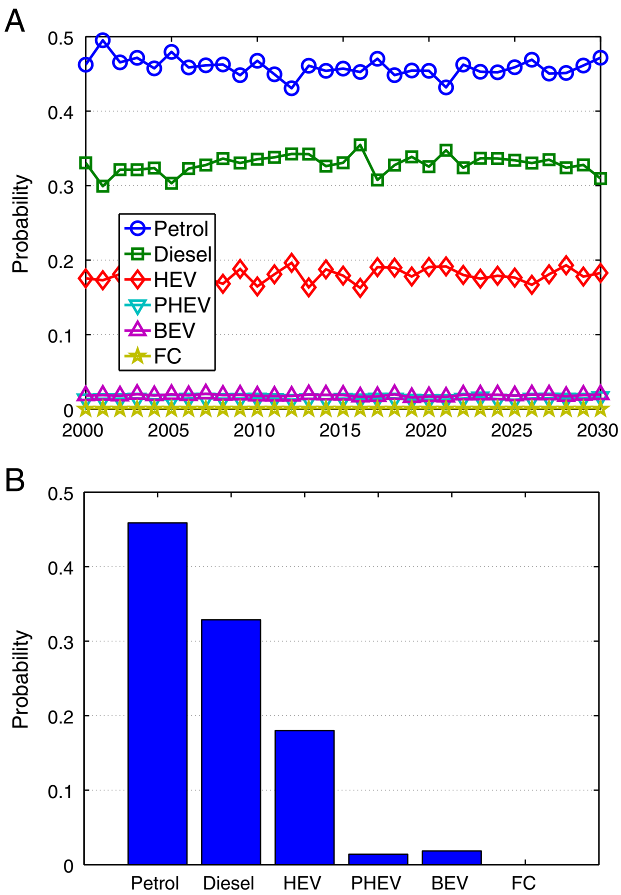


**Fig. 2.** A) Probability of technology adoption for mass-market reference case projected to 2030 and B) arithmetic mean per technology over the projection period.

that influenced HEV adoption. Fig. 3 shows the mean probabilities for each simulation. In the initial early adopter scenario (S1) mean probabilities are petrol (34%), diesel (39%), HEV (23%), PHEV (2.5%), BEV (2.7%) and FC (<1%). All competing technologies take market share away from the dominate petrol vehicle with diesel and HEVs both increasing the most at ~5% each, while PHEVs and BEVs each double their shares to ~2.5%. Other results show that when accounting for higher average incomes, lower fuel prices and fuel consumption as motivating factors, HEVs become the most competitive in the early adopter market surpassing petrol and diesel (S3). This coincides with findings that indicate that typical Prius adopters were not significantly different from

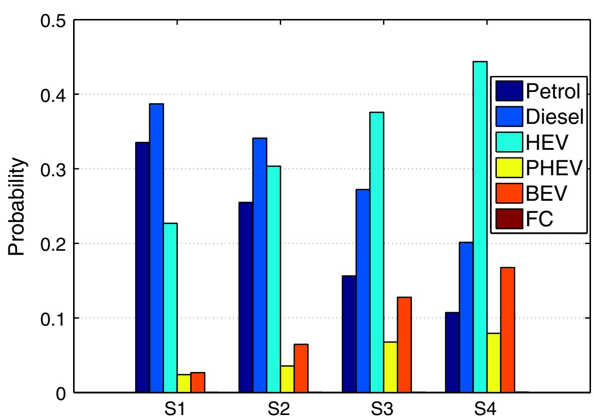


**Fig. 3.** Comparative early adopter scenarios showing income effects (S1) and consumer preferences for lower fuel price (S2), fuel consumption (S3) and $CO_2$ emission (S4) vehicle attributes.

**Table 4**
Incremental change in mean adoption probabilities between initial early adopter scenario (S1) and reference case (Ref) and between subsequent early adopter scenarios (S1-S4).

| Change in probability | Petrol (%) | Diesel (%) | HEV (%) | PHEV (%) | BEV (%) | FC (%) |
|---|---|---|---|---|---|---|
| $P\Delta_1$ | −12.3 | 5.8 | 4.7 | 1.0 | 0.82 | 0.010 |
| $P\Delta_2$ | −8.0 | −4.6 | 7.7 | 1.2 | 3.8 | 0.020 |
| $P\Delta_3$ | −9.9 | −6.9 | 7.2 | 3.2 | 6.3 | 0.010 |
| $P\Delta_4$ | −4.9 | −7.1 | 6.8 | 1.2 | 4.0 | 0.020 |

Notes: $P\Delta_1 = S1 - Ref$, $P\Delta_2 = S2 - S1$, $P\Delta_3 = S3 - S2$, $P\Delta_4 = S4 - S3$.

other consumers except that they were more strongly motivated by the financial benefits associated with HEVs savings from improved fuel economy [11]. When preferential weighting is given to environmental sensitivity (S4), BEVs surpass petrols, PHEVs, and FCs but are not able to outcompete diesels and HEVs, which are cheaper and have far better refuelling availability.

Table 4 shows the incremental change in adoption probabilities between each simulation. Building from the reference case, each consecutive simulation (S1–S4) holds the parameters of the previous simulation constant in order to see the incremental difference that each factor makes on adoption. When looking at the difference between the reference case and the initial early adopter category ($P\Delta_1$), which accounts for higher incomes among early adopters, petrol's share decreases by 12.3% while increasing the share of all other competitors. This reflects more risk adverse early adopter behaviour willing to move away from the incumbent system and test new unproven technologies. When looking at the factors that make the largest incremental impact on adoption within the early adopter market comes from lower fuel prices causing a 7.7% increase in adoption of HEVs shown in ($P\Delta_2$). This is consistent with empirical findings that HEV adopters while being more financially savvy [11] might still reflect general consumer behaviour by placing greater emphasis on short-term financial savings at the pump, rather than longer-term savings from improved fuel economy [25,26]. The largest impact from improved fuel economy ($P\Delta_3$) is for PHEVs (3.2%) and BEVs (6.3%) because these technologies have the largest performance advantage over ICEs. The incremental change from sensitivity to lower $CO_2$ emissions ($P\Delta_4$) while having positive effects on HEVs (6.8%) and BEVs (4%) has far less impact on PHEV adoption (1.2%). That is because HEVs and BEVs outperform PHEVs in WTW $CO_2$ emissions based on our parameter assumptions. This would likely hold true in most instances between BEVs and PHEVs, but would change between HEVs and PHEVs under different emission assumptions. Nevertheless, the slight difference in assumptions between HEV and PHEV in WTW $CO_2$ emissions would not change the overall adoption trend between those two technologies since the mean probability of HEV adoption is far greater than for PHEVs. In summary, what all this suggests is that early adopters may be more motivated by financial savings rather than environmental behaviour. This could inform how new AFVs are marketed by appealing to economic sensibilities in addition to relying on pro-environmental behaviour to motivate adoption.

### *4.3. Mass adopters*

In the mass adopter scenarios we remove income effects but maintain the optimistic assumption that the mass-market still values the financial and environmental benefits associated with AFVs, but now equally weigh those factors against the attributes that typically make ICEs attractive. This includes, performance and reliability which we proxy as vehicle acceleration (S5) and range (S6). We first apply preferential weighting for acceleration and then range to see the incremental effect of each factor shown in Fig. 4.

The situation dramatically changes when performance is accounted for (S5) with petrol's once again leading the market at 34%, followed by HEVs at 33% and diesels at 22%. BEVs and PHEVs both fall below 10% of market shares and FCs are <<1%. This is

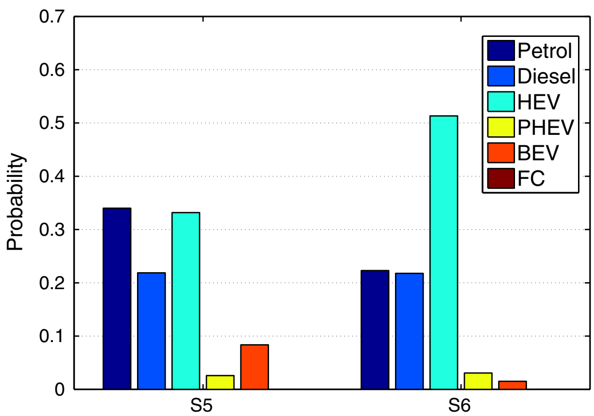


**Fig. 4.** Mass adopter scenarios with preferential weight given to performance (S5) and range (S6).

consistent with empirical surveys that indicate consumers strongly value the overall performance of ICEs [5,9]. When we account for reliability proxied by range (S6), HEVs leap ahead once again because they have a longer range than petrols and diesels and are competitive across all other attributes. This reflects various indications that HEVs are quickly becoming competitive and might achieve significant market penetration in coming years [1,3,7]. In the UK, for example, from 1999 to 2008, annual per annum growth of HEVs was ~50% compared to petrols at 1% and diesels at 10% [23]. However, HEVs still only make up a small fraction of the total vehicle stock in Europe and North America [5]. The mass adopter scenarios show that consumers place high importance on the superior performance and reliability associated with well-proven ICE technologies. Moreover, the rise in HEVs and PHEVs and the decline in shorter range BEVs in S6 show the importance of overcoming range anxiety to trigger adoption. In a recent US survey, 54% of respondents indicated that they would not consider purchasing AFVs until charging locations are as accessible as petrol stations are today [9]. Widespread refuelling availability will therefore be a key enabler for AFV diffusion. We now turn to the effects of increasing refuelling availability for AFV diffusion shown in Fig. 5.

We can see that the largest impact from increased refuelling availability is on BEVs which increasingly takes market share away from ICEs and are able to surpass diesels even with 30% less refuelling availability shown in Panel A (70%). In the same scenario, PHEVs fall far behind since they are less competitive than BEVs in all other attributes, especially purchase price, but petrols and HEVs remain the most competitive taking ~28% each of the total market. This shows that even with large-scale deployment of refuelling infrastructure, unless AFV purchase prices become more competitive, consumers still prefer ICEs. Panel B shows the coupled effects of decreasing purchase price and increasing refuelling opportunity. PHEVs are now able to compete with petrols and diesels and FCs finally begin to penetrate the market. The only scenario where a non-ICE alternative dominates the market is when there is 60% refuelling availability coupled with an almost 80% decrease in the current purchase price of a BEV shown in Panel B (60%). What is important to note is that this assumes that there are not further decreases in the purchase price of ICEs. But if the relative difference can be achieved, where BEVs can close the price gap to within 20% of an in-class petrol combined with 60% refuelling availability, at least from the perspective of a consumer who is also motivated by competitive fuel economy and environmental performance, BEVs become the market forerunner. This means that even if we assume a population of financially and environmentally motivated consumers, these scenarios show the primary importance of decreasing purchase price and addressing range anxiety to trigger large-scale adoption of AFVs.

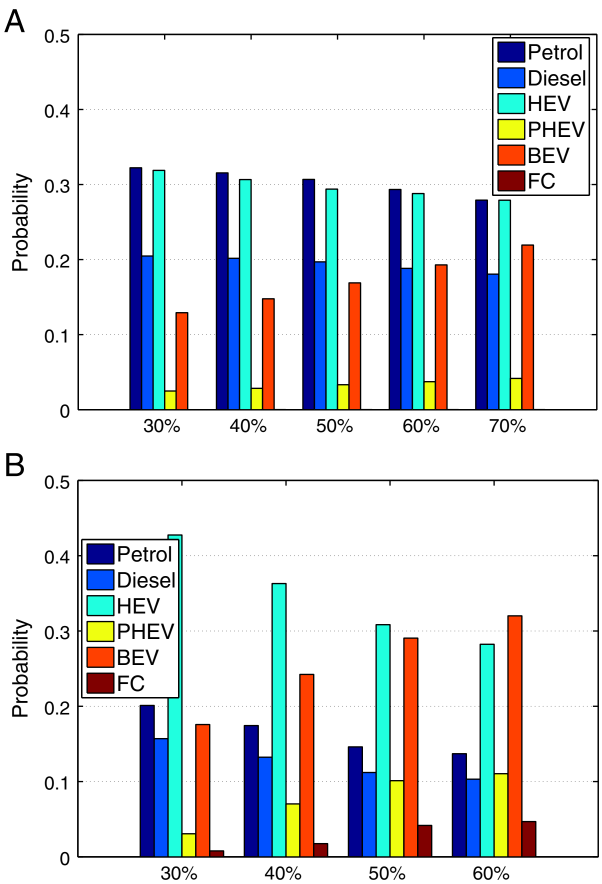


**Fig. 5.** A) Adoption probabilities with increasing refuelling availability for PHEVs, BEVs, and FCs and B) the combined effects on adoption with increasing refuelling availability and decreasing purchase price.

## 5. Conclusions and further research

It has been suggested that PHEVs may serve as a transition technology towards BEVs primarily through cost reductions in battery systems [3,27]. Interestingly our scenarios consistently show BEV outcompeting PHEVs at least from the perspective of the consumer. This is an open question as different manufacturers pursue different market segments. PHEVs have the advantage of range over a BEV, but when taking all other attributes into account our results show BEVs to be the forerunner. However, an important assumption that we make is that as charging facilities become more available, this will offset consumer expectations for a longer-range vehicle. This implies that range anxiety is mitigated by charging opportunity rather than longer-range vehicle capability. Although this may be true in some circumstances such as short urban commuting, it is likely that some consumers would still expect longer-range vehicles for different activities such as week end activities or holidays. Recall also that for some early adopters, HEVs were their second vehicle. Our results would most likely differ if we were to assess different niche markets where longer range PHEVs may out compete BEVs. An area for further research would be to assess the competitiveness of each technology as a function of trip journey purpose and how these trip journey's may change in the future from different demographic or lifestyle trends.

We have shown the effects of decreasing purchase price and increasing refuelling availability on adoption behaviour. It is important to note that our refuelling availability metric used in the model does not necessarily imply a specific number of AFV refuelling stations relative to ICEs since it would have to be normalized against vehicle range. By doing this we could then infer the level of infrastructural investment required to support adoption of AFVs. This would require a spatial analysis coupled with vehicle range and trip length as a function of trip journey purpose, which is outside the scope of the current study. However, our analysis does suggest how important it is to mitigate range anxiety for the consumer's purchasing decision. Specifically, our analysis quantifies the relative importance of refuelling infrastructure and overall vehicle reliability in comparison to other vehicle attributes from the consumer's perspective.

We have also not accounted for changes in other technological attributes such as acceleration, range or increased vehicle efficiency. As these attributes improve for AFVs, it is likely that this will have a positive influence on adoption. But we cannot discount further ICE improvements, which will also make them increasingly attractive to consumers from both an economic and environmental perspective. Further research would be to assess the learning curves for each vehicle technology and how their evolving attributes may influence adoption behaviour in the future [28]. Furthermore, we have simply assumed global preferential behaviour in our scenarios, but it is important to understand the underlying mechanisms that might lead to preferential behaviour. We have become increasingly aware of the role that social networks play in diffusion behaviour [29–31]. This could give insight into how social networks may act as a mechanism to positively influence adoption of AFVs or other advanced energy saving technologies to meet energy policy.

Major government incentives are now in place to reduce the purchase price of AFVs. However, subsidies are not sustainable over the long term for inducing mass adoption [32]. Energy systems analysis generally relies on macro-economic models to assess the uptake of new technologies where consumers are often treated as homogenous agents responding primarily to differential price signals [33,34]. But empirical [35] and theoretical [12] work demonstrates that adoption behaviour is far more complex with a high degree of market heterogeneity. We show how probabilistic computational techniques such as Monte Carlo simulations and scenarios can be used to model a wide variation of consumer behaviour, thereby disaggregating the market giving insight into both the technological and behavioural factors that might lead to mass diffusion of new innovations. Consumer surveys indicate that people are not willing to adopt AFVs until adequate charging infrastructure is in place. This study has shown the possible scale of infrastructure development necessary to trigger widespread adoption of AFVs. These scenarios in a sense are also highly optimistic because they assume a consumer profile that is positively influenced by attributes that give market advantage to AFVs. Yet, even under these optimistic assumptions ICEs remain competitive. This shows the massive level of behavioural change necessary to induce large-scale adoption. This work contributes to the policy discussion by questioning some of the highly optimistic projections by governments and industry that suggest the transport system can be transformed rapidly. Our results infer the high level of commitment by government and industry necessary to achieve their stated goals, and that policies and strategies targeting consumer behaviour will need to be deployed in addition to technological efficiency improvements.

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