# Working Paper

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**The use of Stated Preferences to forecast alternative fuel vehicles market diffusion: Comparisons with other methods and proposal for a Synthetic Utility Function**

# The use of Stated Preferences to forecast alternative fuel vehicles market diffusion: Comparisons with other methods and proposal for a Synthetic Utility Function

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**Abstract:** Stated Preferences are, together with Bass diffusion and, to a lesser extent, Total Cost of Ownership, the most popular methods to forecast the future diffusion of electric and alternative fuel vehicles. In this contribution, we compare the merits and limitations of SP relative to other methods. We also review the empirical results provided by SP surveys and assess their validity for modeling market diffusion. We also propose a meta-analysis-based Synthetic Utility Function that consolidates results across various studies and can be used, for simulation purpose, in a Discrete Choice Model context. Such an approach makes the simulation results less dependent of single surveys' idiosyncrasies, and hence is helpful for the formulation of robust policy recommendations.

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# Introduction

The interest of policy makers and general public about alternative fuel vehicles has gained strength in the most recent years. This interest concentrates on electric and fuel-cell vehicles together with gaseous fuels and non-fossil liquid fuels (biofuels). The question on how many of these vehicles can really be sold and which policy design can make the best of their diffusion potential has become very relevant for applied economics and transport policy issues. In this context, a large part of the research effort has concentrated on the achievement of Stated Preference surveys to provide necessary information about the purchase behavior of car buyers.

Relating to this development of SP surveys, there are however still a number of open research questions and challenges for practitioners.

First, the merits of SP compared with other competing methods should be carefully investigated. Generally, SP based models would compete with diffusion models à la Bass, or Total Cost of Ownership (T.C.O) computation. These different approaches belong to to separated scientific streams and the adoption of one rather than the others often corresponds to one's belonging to a given scientific community rather than to a well informed decision. Thus, the merits and limitations of SP compared with alternative approaches have to be investigated and discussed in the scientific community so that more informed choices can be made.

Second, if SP is selected as the valid method, the advantage of achieving an *ad hoc* survey should be cautiously weighted. Indeed, as we will try to make apparent in this paper, directing the efforts of transport economists toward consolidating SP results through meta-analysis could be considered at least as relevant on the research agenda as the achievement of additional SP surveys. Analysis of existing SP surveys actually indicates that they exhibit strong idiosyncrasies. Such idiosyncrasies can be linked to the well known framing effects that impact the preferences elicitation process, or to the necessarily limited number of attributes that can be included in a single survey. Whatever the reason, the analyst is at risk, when using outcomes of a single SP survey, to provide non-robust results and/or policy recommendations.

Large part of the present contribution is based on the research project Market Model Electro Mobility (MMEM), a project funded by the Federal Ministry for the Environment and Nuclear Safety to evaluate various electric vehicles (EV) supporting policies and in which these two issues had to be carefully considered. These two issues are considered in detail in this paper. In particular, this paper provides a tractable meta-analysis based Synthetic Utility Function, set up to correspond to consumer preferences in Germany. It is our view that, besides the particularity of the German market, there is a

more general need in the scientific and professional community, to have consolidated, SP-based, consumer trade-off information available, that could be used, with adequate adjustments, in a reasonably large variety of markets.

The structure of this paper is as follows. First, we examine the different competing methods available for alternative fuel vehicles' diffusion forecast and explore the advantages and reasons for success of SP compared with other methods. Second, we make a thorough examination of methodological features of existing SP surveys and show the willingness-to-pay results that have been obtained in various contexts by this method. Third, we develop a Synthetic Utility Function that consolidates results across surveys and is fully functional for simulation purposes.

# 1 – Overview of methods available for alternative fuel vehicles diffusion forecast

In this section, we provide an overview of the different methods available for alternative fuel vehicles' diffusion forecast. Such methods basically pertain to three different paradigms: Total Cost of Ownership (T.C.O.), diffusion theory and Stated Preferences surveys.

## *Total Cost of Ownership*

Total Cost of Ownership approach is based on the comparison of the capital and operating costs among different technologies. In most cases, it assigns the demand to the minimal costs technology. While this approach is fairly simplistic in its assumptions, it has gained popularity especially in studies that come from the industry or from consulting organizations while it has more limited room in the scientific literature (Mock et al., 2009). Reasons for success of this approach relate, in our view, to:
- The reliance on fairly available data. The method relies on fuel costs, taxations, capital depreciation (based on vehicle value and amortizing assumption), parking costs, etc, all items that, to a certain extent, are fairly available to any professional organization engaged into the study of automotive market dynamics.
- The strong adherence of the approach to rational decision making. The approach fits both with the assumption that is cost is a main driver of consumer behavior and that it should be a major concern of public policy decisions.
- The possibility for the T.C.O. analysis to perform very detailed calculation, using large quantity of data. Furthermore, the method is fairly flexible in that any additional piece of information can be integrated without the necessity to reshape the whole approach. As a result, the large number

of variables provides the method a good face value, and sometimes tends to intimidate possible criticisms.

However the method suffers from serious drawbacks, especially considering three points.
- Costs monism: the method assumes that car purchase behavior is merely dictated by cost considerations. This assumption turns out to omit others, non-monetary, attributes which can be found important in various car purchase settings, and especially in the context of new technologies with very distinctive non-monetary attributes (think of the range attribute of electric cars), which can be an important choice criteria.
- Excessive reliance on consumer's rationality: it is well known and documented (Greene, 2010; Turrentine & Kurani, 2006) that potential car purchasers, when considering car related expenses, have a discounting that goes far beyond the one usually observed in other markets. When such a feature is not properly taken into account, the analysis cannot provide valid information on the car purchase decisions.
- Monolithic behavior: T.C.O. typically assumes that two different decision-makers would make the same decision in the same choice situation. This heavily contrasts with direct experience, with the observed diversified structure of car market, and with the state of the art of economic analysis that tends to give full recognition to the interpersonal variations in behavior. Some applications of the T.C.O. model try to overcome this limitation by considering a detailed socio-economic segmentation or introducing some stochastic component. It is only by expending such features that T.C.O. models can avoid the mentioned pitfall.

Interestingly one can also note that a T.C.O. model is nothing more than an (heavily) restricted RUM (Random Utility Maximization) model. Consider a RUM model, where utility of alternative $i$ depends on $K$ monetary attributes $X_{ik}$ and $L$ non monetary attributes $Y_{il}$. The utility can be written as:

$$l, \text{ with } \varepsilon \text{ a distribution of variance } \sigma_\varepsilon \qquad \text{Eq. 1}$$

Then a T.C.O. model is nothing but model written in equation 1 with the following restrictions: $\beta_l = 0 \ \forall \ l$, and $\sigma_\varepsilon = 0$. This makes apparent that T.C.O. is a fairly illegitimate restriction of more realistic choice paradigms.

In conclusion, it is fair to say that T.C.O. is certainly informative of the monetary attributes of the different technologies, but, unless its features are significantly extended, it is of limited relevance for diffusion forecast. Actually the scientific literature dedicated to T.C.O. often recognizes that T.C.O. is not designed for sale forecast.

## *Diffusion theory*

A second series of methods relies on the diffusion theory. Such approaches usually rely on mathematical formulations to represent the progressive

diffusion of a technology from a given observed level to a hypothesized potential. From the different available formulation of this method, the one proposed by Bass (Bass, 1969, 2004; Mahajan, Muller et al., 1990) has gained the strongest weight and is nowadays highly influential in the management literature. Bass approach postulates that new technologies have a given potential which will be reached only progressively, starting from the introduction phase. The diffusion pattern will be determined by two mechanisms: adoption, by which people purchase new technology, and imitation, meaning purchase decision influenced by the current diffusion of the technology.

Such mechanisms can be expressed, in their essence, as in equation

$$n_t = \frac{dN_t}{dt} = p(\Lambda \qquad \text{Eq. 2}$$

with
  · $n_t$: product purchases in period t
  · $N_t$: cumulative product purchases until period t
  ·
  · $M$: (cumulative) market potential in product life cycle
  · $p$: coefficient of innovation
  · $q$: coefficient of imitation.

Litteralty, *(M-N$_t$)* represents the reservoir of clients, that is the difference between the potential and the cumulated achieved sales. This reservoir translates into sales by the effect of *adoption* (a fraction of the reservoir adopts the product at each time period) and *imitation* (purchases increase when more people are in contact with purchasers).

The Bass diffusion approach has gained a lot of popularity and it is fair to say that it is probably the most widely used method, at least in the management science community (although with a high share of unpublished work: Cao, 2004; Lamberson, 2008; Richardson, Mc Alinden et al., 1999; Struben, 2004). Reasons for such a success probably pertain to the influential role of diffusion theory in management and marketing sciences. The method is also attractive because it intrinsically replicates any available information on the current level of the diffusion. When data on the current sales are available it is always possible to use them in the calculation of the diffusion pattern, and the model will intrinsically reproduce these data. This avoids the annoying situation where model produces an estimate for the current time period that is inconsistent with observations. There is however room for discussion on whether this increases the realism of forecasts or whether it is rather an artifact due to the definition of the model, with no implication on its forecast capability. Another reason for the success of the method is that it provides very smooth diffusion patterns, with no

discontinuities, which provides usually a good prima facie value to the results.

There are however some limitations to the method. First, the model does not in itself provide an estimate of the market potential. Actually, this point deserves more discussion as various applications of the method also calibrate M, together with p and q, based on observed time series. But this procedure is not inherent to the Bass approach but rather is often a statistical expedient to identify the potential (Gosh, Hemmert et al., 2011: 36–45).

There are also some issues about the nature of the market potential M that is defined as the cumulative lifetime potential for the product (first time purchases). This raises questions in situations where products have a long lifetime. When considering the car industry the notion of total cumulated sales for a technology is a challenging if not an unrealistic one: on how many years should these sales be computed ? Correspondingly, it is inherent to the Bass model that the product sales are modeled on the whole life cycle of the product. There will be a startup phase, a mature product development, a declining phase of the sales. This implies that the Bass diffusion model will produce a phase where sales decrease. This may be difficult to accept for products with a very long lifetime horizon. Examination of available applications of the method illustrates that practitioners deal with this issue in a number of ways where the initial conceptual consistency of Bass approach may be at risk.

Also, from a conceptual point of view, many of the applications of Bass diffusion model are unrealistically unresponsive to changes in competing alternative. Often the market potential M is defined irrelevant of the competing alternative attractiveness which can be found very restrictive.

## *Stated Preference Surveys*

The third approach is based on Stated Preference methods. SP are survey methods where the consumer is asked to express its preferences among different alternatives (e.g.: cars) defined by attributes (e.g.: speed, price, range). Using the answers provided by interviewees, the analyst can infer information about the trade-offs made by the consumers among the different attributes (for instance how much range can they forego to save in purchase price). Usually one of the attributes of the alternatives is price, allowing for the computation of willingness-to-pay for the other attributes.

SP have flourished in a number of varieties and with a number of labeling: Conjoint Analysis, Choice Based Conjoint, Stated Preference (although these different names capture differences that are sometimes relevant, we will use, unless specified explicitly, these different labels as synonym for the sake of

this article) that share a common conceptual setting: analyzing preferences of consumers based on preferences among hypothetical attribute combinations. Stated Preference data are usually used within the Discrete Choice, Random Utility Maximization framework.

Stated Preferences are usually seen as an alternative to Revealed Preferences. Revealed Preferences rely on actions actually performed by the consumer and Stated Preferences are based on intentions expressed when facing hypothetical situations. While Revealed Preferences offer a number of advantages, economists have accumulated experience in the latest decades that indicate that a well-designed SP survey can supply useful information (a seminal presentation of this can be found in (Kroes and Sheldon, 1988). Noticeably, they appear suitable to generate larger datasets than RP within a given budget constrain, which result in smaller confidence intervals for the values of interest. Moreover, in many situations where the good has not been introduced yet in the market, no Revealed Preferences data are available, and SP offer an adequate (if not the only) alternative (Hensher, Rose et al., 2005).

Apart from the inexistence of Revealed Preference data (which would not in itself be a merit of Stated Preferences), SP offer a number of advantages compared with competing approaches for the sake of alternative fuel vehicles diffusion forecast. First, they provide information about the effect of non-monetary attributes. As long as an attribute is present in the SP survey, information can be extracted on how it impacts the consumer choices. This appears to be of crucial importance in the case of electric cars, in that they have some non-monetary features (range, refueling time, etc) that make them very distinctive from conventional cars. Second, SP are intrinsically calibrated to some consumer choice data. This contrasts with T.C.O. that, strictly defined, is not calibrated to behavioral information, and with Bass diffusion model which sometimes are, but sometimes are not, calibrated to ad hoc data. Third, SP surveys results replicate consumers' preferences in given market conditions. This can be an advantage in situations where the decision maker is interested in consumer response in a given setting. For instance, he is interested in purchase intentions relating to a given national or regional market, or in a given period of time, or he can be interested in the effect of certain specific attributes. One advantage of SP is that it is easy to tailor the data collection process to the market conditions of interest. Forth, SP are intrinsically attribute responsive, both considering the alternative of interest and its competitors, this means that the forecasted choice probability of a given alternative will always be dependent on the level of the attributes in consideration.

Parallel to these advantages, some potential drawbacks of SP survey are discussed in the literature. This relates primarily to the hypothetical distortion that may take place in the survey. In some occurrences it is possible to correct for possible hypothetical distortion by performing an additional calibration of the model on real world data. This usually occurs

through the calibration of an Alternative Specific Constant to actual market share. This technique is however of little help for alternative fuel vehicles in that market share are close to 0. How to take into consideration the possible effect of hypothetical distortion for AFV diffusion forecast is still on the agenda of transport economists. Additional to hypothetical distortion, a slightly more elaborated effect relates to the framing effects that make SP results strongly dependent of a survey *modus operandi*. This issue may result in a warning about using uncritically outcome of a given SP survey, a line of argumentation that partly motivates the current paper, as will be apparent in the next sections. These issues should however not be exaggerated. Generally, the scientific literature has gathered a number of evidence that, despite these issues, SP exhibit a good level of predictive validity (for a survey, see Massiani, 2005: 141–149).

## 2 –SP surveys for electric and alternative fuel vehicles: State of the art and meta-analysis

The advantages of Stated Preferences have resulted into an increasing number of applications. Existing surveys that were considered in this paper are listed in Table 1 with a distinction between three categories of works: academic peer reviewed publication, other academic papers and applied forecasting studies.

**Table 1 – List of SP surveys considered**

| Academic peer reviewed publications: | Other academic papers: |
|---|---|
| Beggs and Cardell, 1980 | Golob, Kitamura et al., 1991 |
| Train, 1980 | Knight, 2001 |
| Beggs, Cardell et al., 1981 | Batley and Toner, 2003 |
| Calfee, 1985 | Adler, Wargelin et al., 2003 |
| Bunch, Bradley et al., 1993 | Horsky, Nelson, et al., 2004 |
| Ewing and Sariloglu, 1998 | Knockaert, 2005 |
| Tompkins, Bunch and al, 1998 | Kuwano, Zhang et al., 2005 |
| Brownstone and Train, 1999 | Högberg, 2007 |
| Brownstone, Bunch et al., 2000 | Achtnicht, Bühler et al, 2008 |
| Dagsvik, Wennemo et al., 2002 | Hess, Fowler et al., 2009 |
| Batley, Toner et al., 2004 | Achtnicht, 2009 |
| Zito and Salerno, 2004 | Dagsvik and Liu, 2009 |
| Potoglou and Kanaroglou, 2007 | Ziegler, 2010 |
| Ahn, Jeong et al., 2008 | |
| Axsen, Mountain et al, 2009 | Applied forecasting: |
| Caulfield, Farrell et al., 2010 | |
| Mabit and Fosgerau, 2011 | IMUG, 2010 |
| Hidrue, Parsons et al., 2011 | Öko-Institut and ISOE, 2011 |

From a methodological point of view, two types of consideration can be made, the first one relates to the design of the survey, the second one to the data processing.

## *Review of survey design practice*

The examination of the existing survey designs leads to mixed conclusions. On the one hand, it seems that some of the specific features of alternative fuel vehicles are sometimes neglected. On the other hand, there is often a focus on environmental performances, which, to our view, may be deceptive. These issues are discussed more in details in the paragraphs below.

First, existing SP surveys consider some, but not all, of the features that make alternative fuel vehicles differ from conventional vehicles. Some attributes that are probably fundamental for electric vehicles are often absent. Range is absent from various surveys (Achtnicht, 2009; Achtnicht, Bühler et al., 2008; Ahn, Jeong et al., 2008; Axsen, Mountain et al., 2009) while it is usually thought to be one of the strongest limitations of electric cars. This absence is sometimes supplemented by the introduction of some correlated attribute like the density of refueling stations (Achtnicht, 2009; Achtnicht, Bühler et al., 2008), but there is room for discussion on whether this can suitably represent the effect of range. Additionally, considering refueling stations, there are some issues about how interviewees understand this attribute: Is it for instance implicit for them that refueling operations will be as quick as for conventional cars? Another important feature of alternative technologies relates to the existence of a series of "transition" technologies: mainly Plug-in Hybrids (PHEV) or Range Extender, and, to a certain extent, Hybrid. In existing SP studies, available technologies are usually introduced whether through a fairly exhaustive set of competing technologies (CNG, LPG, Biofuels, Hydrogen, etc as in Achtnicht, 2009) or through a limited choice between conventional and electric technologies, mainly Battery Electric Vehicles (BEV) and Hybrid. Interestingly, we find that the existing surveys give usually no room to transitory technologies, especially considering PHEV. This element could be a major concern for the reliability of Electric Vehicle diffusion forecast. Actually, it is found that when these intermediate technologies are introduced in the survey they achieve a significant market share, usually larger than BEV (Öko-Institut & ISOE, 2011).

Moving toward other attributes, various surveys introduce environmental performance: often expressed in $CO_2$ emissions (Achtnicht, 2009; Caulfield, Farrell et al., 2010; Öko-Institut & ISOE, 2011) or some relative emission reduction ("*Tailpipe emissions as fraction of comparable 1995 new gas vehicle*" in Brownstone et al. (2000), "*fraction of emissions*" of existing car in Batley & Toner (2003)).

More surprisingly, compared with mainstream SP practice, we find a number of surveys that do not use purchase price as an attribute (Ahn, Jeong et al., 2008; Caulfield, Farrell et al., 2010 consider road tax and fuel expenditure as cost attributes). In such cases, cost appears only through other items like maintenance cost (Ahn, Jeong et al., 2008) or fuel expenditures and Vehicle Road Tax (Caulfield, Farrell et al., 2010). There are some issues on whether this can be an appropriate approach. It is unsure how interviewees elaborate some implicit assumptions about the value of the price attribute. For instance, is price considered equal among the different alternatives, or is it considered equal to some a priori, possibly uninformed, values?

We also find that there is usually no room in the choice process for vehicle segments (for instance: compact against mini) or any similar attribute that would capture how segment shift can be an alternative to technology shift.

Such a shift would replicate the fact that, if conventional fuel is getting more expensive, one may choose to switch to a smaller car rather than opting for an electric car. Such trade-offs are not reflected in the SP surveys when they omit this choice dimension.

To conclude, it emerges from the analysis of existing surveys that there may be some failure to take sufficiently into account certain peculiarities of alternative fuel vehicles, with special concern for range and existence of transition technologies.

As an aside, considering methodological issues, one may add that most of the surveys are based on orthogonal designs, so a potential improvement of the surveys would be to elaborate on the current development of the experimental design optimization (Rose and Bliemer, 2009).

## *Data processing*

In this section, we consider data processing issues, that is, the use that can be made of the data once they are collected.

We first consider the form (i.e. linear, interacted, etc) in which the various attributes are introduced. The different attributes are often introduced in linear forms and temptation to do differently often proves disappointing (for introduction of squared terms, see for instance: (Batley, Toner et al., 2004) "*none of the squared terms was found to be significantly different from zero*"). Attempts to find non-linear effects usually focus on price: (Ziegler, 2010) introduces log(price). While this formulation may be supported by the data it is against micro-economic expectations in that it assumes that marginal utility of money would be increasing[1]. Apart from income, other studies explore, in a limited number of applications, non-linear effects of fuel costs, or range (Bunch, Bradley et al., 1993, find a significant coefficient both for Range and Range squared).

Interactions with socio-economics are often absent. Sometimes several models are calibrated based on different socio-economic groups (Dagsvik, Wennemo et al., 2002) while in some other cases, socio-economic covariates directly interact with attributes (Achtnicht, Bühler et al., 2008). Mabit and Fosgerau make an in depth analysis of interactions by testing interaction of individual or household characteristics with attributes, including technology (Mabit and Fosgerau, 2011). They found significant negative interactions between "acceleration time" and "male", "price" and "child in household",

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[1] When the price increases, the income available for other expenditures decreases, the goods that are purchased have a higher marginal utility thus the marginal utility of money increases. Yet, one possible motivation for introducing decreasing effect of price could be to represent difference of valuation among different buyers. This point would deserve further analysis.

"price" and "single". Positive interactions were found between "range" and "age<30", "price" and "high income household".

In some applications, income is interacted with price. It is introduced to normalize purchase price (price/log(income) in Brownstone, Bunch et al. (2000); see also Axsen Mountain et al. (2009). The introduction of the logarithm of income as a denominator to price implies that the marginal (negative) utility of extra cost (= minus the marginal (positive) utility of income) is an isoelastic function of income with elasticity equal to 1, an assumption that finds increasing support in many studies of inequalities and inter-temporal choice. Concluding on interactions, the State of the art reflects two features. First, like for non-linearity, efforts to capture them are not always bringing to the conclusive results that one may expect. Second, many of the consumer features, that arguably have a strong influence on the choice, are usually not present in the models. For instance, the difference between first car and second car purchase is present only in Ramjerdi and Rand (1999). The effect of garage ownership on electric car purchase is usually absent with only few exceptions (Zito & Salerno, 2004).

## *Willingness to pay estimates*

In this section, we illustrate the WTP's that result from available SP surveys. As is well known, WTP expresses the marginal rate of substitution between any good (or attribute when considering multiattribute goods) and the numeraire. It can be expressed as the ratio of the marginal utility of a good and the marginal utility of income. The next table provides the WTP's retrieved for the main attributes of alternative fuel vehicles across a number of recent SP surveys. Results are homogenized in € 2009 based on PPP conversion rates and inflation in each country.

**Table 2 – WTP Estimates across different surveys (€ 2009, author's computation)**

| Attribute | | Achtnicht, 2009, 2010 (Germany) | Brownstone et al., 2000 (b) (California) | Dagsvik et al., 2002 (d) (Norway) | Axsen et al., 2009 (a) (Canada+California) | Batley & Toner, 2003 (s) (UK) | Batley et al., 2004 (r) (UK) | Mabit & Fosgerau, 2010 (Denmark) | Knockaert, 2005 (Belgium) | Unit (Euros 2009 prices) |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable costs | Fuel costs | -1938 | -934 | | | | | | -992 | (€/ €/100km) |
| | | | | | -4,9 | | | | | (€/ €/yr) |
| | | | | -1049 | | | | | | (€/ l/100km) |
| | Annual cost | | | | | | | -4,2 (c) | -4,7 | (€/ €/yr) |
| | Running Costs | | | | | -758 | -244 | | | (€/ €/100km) |
| | Service | | | | | | | 2336 (e) | | (€) |
| Emissions | CO2 emissions | 52 (f) | | | | | | | | €/ g/km |
| | Pollution/Emissions | | -71,2 (h) | | | -330 | -90 (q) | | -80 (g) | €/% of conv veh. |
| Service Stations | | 63 | 73 | | | | 166 | | | €/% stations |
| Range | Range | | 4235 (t) | 1714 | | 9813 | 2099 | 1467 | 2426 | €/100km |
| Performance | Acceleration (0-30 mph) | | -1509 (p) | | | 235 (o,f) | | | | €/sec. |
| | (0-100kmh) | | | | | | | -614 | | €/sec. |
| | Top speed | | 99 | 7 | | 393 | 63 | | | €/ km/h |
| | Motor power | 157 | | | 70 | | | | | €/hp |
| Technology: ICE | Generic ICE | | reference | reference | reference | | | reference (k) | | |
| | Gasoline | 262 | | | | | | | reference | € |
| | Diesel vehicle | reference | | | | | | | 4307 | € |
| Hybrid | | -4047 | | 3341 | 32741 | | | 5961 | 23 | € |
| | | | | | -10289 (j) | | | | | € |
| Gaz | | -6111 (n,l) | 5588 (n) 9713 (m) | 2273 (l) | | | | | -7636 (l) | € |
| Bio fuels | Biofuel vehicle | -10874 | | | | | | 4222 (i) | | € |
| | Bio-diesel | | | | | | | | | € |
| Hydrogen | Fuelcell vehicle | -5139 | | | | | | 10336 | -1398 | € |
| Electric | Electric vehicle | -13672 | -165 | 1128 | | | | 7409 | -3750 | € |
| Alternative Fuels | | | | | | | | | -3086 | € |
| Refueling | If refuel location at home | | | | | | | -8676 (u) | | € |
| | Time for a full refuel | | | | | -116 | | | | €/min. |
| | Refuel once every 2 days | | | | | | | 3474 (v) | | € |
| | Refuel once every 4 days | | | | | | | 6016 (v) | | € |
| | Refuel once per week | | | | | | | 8617 (v) | | € |
| Trunk volume | | | | | | | | | 92 (w) | €/% of conv. car |

(a) Computed for income = 78000 US$  (b) Computed at average sample income 38000 US$  (c) Mabit & Fosgerau: maintenance, fuel expenses, taxes.  (d) Weighted average of six models based on six different age-gender groupings  (e) Mabit & Fosgerau. 2010: if extra service and repairs other than maintenance is included in annual cost  (f) Non significant coefficient.  (g) % of diesel or gasoline car.  (h) "Tailpipe emissions as fraction of comparable 1995 new gas vehicle". Converted in €/% in our table.  (i) Biodiesel.  (j) California.  (k) In Mabit & Fosgerau (2010) the fuel-specific constants capture pollution effects for the different alternatives.  (l) lpg.  (m) methanol.  (n) CNG.  (o) 0-60 mph.  (p) 0-30 mph.  (q) wtp for a reduction in a 1-10 range of emissions is converted into % assuming 1-10 range represents 0-100 %.  (r) model 4. MXL merging two databases.  (s) Table 2: "MNL based on full data set following cleaning".  (t) at mean range.  (u) compared with petrol stations.  (v) Compared to refueling every day.  (w) Knockaert (2005) reports "percentages", understood as "fractions", so values calculated from coefficients reported in Knockaert (2005) are divided by 100

# 3 - Proposal for a Synthetic Utility Function

In this section, we use Willingness-To-Pay data resulting from our meta-analysis in order to construct a Synthetic Utility Function. Using a Synthetic Utility Function is an alternative to the more traditional approach of calibrating a specific utility function based on a given field survey, and, as will be illustrated below, allows for more robust diffusion forecasts.

Examples of Synthetic Utility Functions applied to alternative fuel vehicles can be found in a few studies: (AECOM Australia, 2009; Motivforschung & Prolytic, 2010). To our view, results of these latest contributions can be expanded by elaborating on a larger number of surveys and being more systematic in the data exploration. Additionally, most of the WTP's proposed in these applications were linear, assuming constant valuation of attributes. Also, we posit that such methods would deserve to be submitted to scientific scrutiny, a process that did not go through until now and that the present article is partly trying to achieve. Additionally, these contributions are only partly adequate to be used on a European market (they typically blend results of North-America and Oceania together with European data producing results that may not be adequate for any of these areas). In our analysis, the Synthetic Utility Function is tailored to correspond to market conditions prevailing in Germany. Its outcome can be used, provided adequate consideration for local conditions is made, to market conditions prevailing in various European countries.

Advantages of using a Synthetic Utility Function, compared with using results of a given SP survey, are:
- It provides results that are less dependent of the elicitation process of a given SP survey. The results we presented in our meta-analysis indicate that survey design may influence strongly the valuation of certain attributes (suppose for instance the impact of refuelling network, when range is not among the survey's attributes). Then there is a risk that relying on one single survey gives too much importance to idiosyncrasies of the survey.
- It overcomes the limitation of a given SP survey to include only a limited number of attributes. This allows the analyst to rely on a more comprehensive set of attributes.
- It allows using information available through non SP survey data (for instance hedonic prices or Revealed Preferences coefficients can be used in order to check, validate and filter existing data).

These advantages can be obtained at the price of additional difficulties, two of them being especially relevant. First, in order to retrieve a utility function from a set of WTPs, one needs to set some identification constraint (otherwise infinity of utility functions could be suitable). One solution to this issue is to use empirical information about elasticity to some attribute (usually price) in order to scale the utility function. Second, one needs a representation of correlations among alternatives. WTP information does not provide such information. In the likely situation where Independence of Irrelevant Alternatives property does not hold, the modeller needs to input some correlation in the model. This has to be done using information that are not provided by WTP's but typically relate to the substitution patterns of the consumer. In the present paper, we will not investigate more in detail these two issues that need careful consideration (for a complete description see: Gosh, Hemmert et al., 2011), but we will concentrate on the formulation and quantification of the utility function.

## *Marginal value of the different attributes*

In this section, we propose a series of WTP for various attributes, based on the meta-analysis of existing survey supplemented with adequate micro-economic information. While meta-analysis usually relies on statistical analysis of an effect size, the existing quantitative results do not appear sufficiently numerous to perform a formal quantitative analysis. Thus we can only use a more informal, judgmental, aggregation considering the different results at stake and comparing them. This approach may evolve in the close future into a more formal analysis considering the growing number of SP surveys that are currently achieved in various contexts and countries.

We consider range, refuelling stations network, car performance, operating costs, emissions, alternative specific constant and eventually we analyse how (lack of) diversity (number of models available in one technology) can be taken into account in a Synthetic Utility Function.
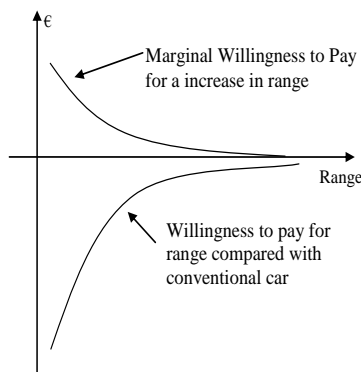
### Range
Range, together with refuelling network, defines autonomy of each vehicle's technology. These two attributes probably interact (the less refuelling network is dense, the more it is important to have a large range), but we expose them in sequence.

The a priori expectation is that the marginal impact of limited range (compared to conventional cars' ranges) should be large

for low ranges and become smaller when the range increases, until it becomes negligible when the range has reached a level comparable with conventional cars. The aspect of such a relationship is depicted on Figure 1 that displays both the marginal and cumulated willingness to pay for range[2]. For simplification purpose, and considering it does not impair the validity of the approach, we will not consider very low values of range but consider only range lager than 50 km.
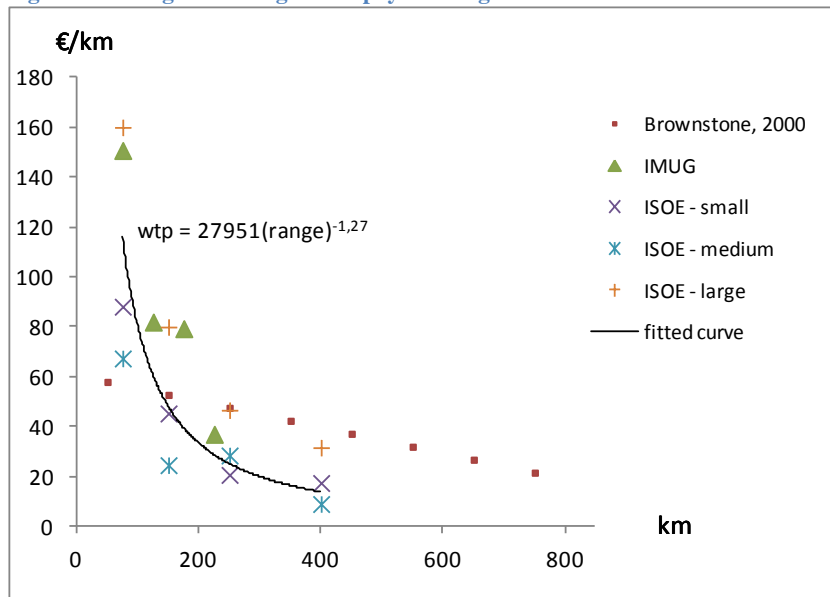
Figure 1 - willingness to pay for range



Paradoxically, range is absent from numerous studies and has a linear value in the largest part of the existing literature (Brownstone and Train, 1999; Dagsvik, Wennemo et al., 2002; Mabit and Fosgerau, 2011) interact age with range. Other studies (Greene, 1994) consider that range disutility can be approached through the extra refuelling time needed, a statement that may be reductive compared with the true inconvenience of range limitation. Given the limited results available on range marginal valuation, any consolidated statement about range is a challenge. Available data suggest an average WTP in the range €20 – €160/km but this interval is large and it does not accommodate for the decreasing marginal value of additional range. Information on such decrease can be found in a very limited number of studies (Brownstone, bunch et al., 2000; IMUG, 2010; Öko-Institut & ISOE, 2011). The outcomes of these three studies are displayed on Figure 2. This figure also depicts a regression of marginal willingness to pay for range, based on IMUG and ISOE (average of the three car segments) data. We concentrate on these latest two data sets in order to make a recommendation closer to preferences prevailing in nowadays European markets.

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[2] The graph is merely illustrative. The fact that the cumulated willingness to pay is negative is not in itself a feature of the function, as it depends on the "reference" range value with which a given car is compared.

Based on the IMUG and ISOE (average of three car segments) data, marginal Willingness-To-Pay for range can be estimated as:

$$wtp = 27951(range)^{-1,27} \qquad \text{Eq. 3}$$

This estimate is produced with a limited degree of freedom, and it is hoped that in the near future, more data will be available to estimate such a relationship. Additionally, this estimate could be further improved by taking into account the change in WTP for ranges between 400 and 1000 km, values that are usually not considered in the available literature. Such an extension of this function may prove non-futile as some technologies typically have range that can go up to 1000 km.

## Refuelling network

Together with range, refuelling network is the other attribute that defines autonomy of the vehicles. Accepting the simplifying assumption that these two attributes do not interact, one should at least take into account two aspects of the refuelling network: the station density and the refuelling duration. Focusing on electric vehicles, one should at least consider two extreme cases of refuelling duration: Ultrafast reload (10 minutes for 80% of battery capacity), and normal (6-10 hours for a full reload), while fast reload may constitute (2 hours for a full reload) an intermediate situation. Eventually, one should consider that reloading can take place in different situations (Home plugs, Office plugs, Street plugs). Most of the results available in the literature do not explicitly specify what type of refuelling facility is considered which is a hindrance to the proper valuation of this attribute. In those situations, it is likely (although it cannot be demonstrated at this stage) that respondents will consider

refuelling conditions that are similar to the ones they experience with conventional fuel vehicles. This means that the Willingness-To-Pay for an increase of refuelling facility should be interpreted as a Willingness-To-Pay for Ultra-Fast Charging. Correspondingly, the Willingness-To-Pay for other refuelling technologies should be much lower. We present hereafter an approach to include Ultra Fast Charging in the Synthetic Utility Function and propose in appendix 2 a solution for considering also Fast Charging.

Sticking to the hypothesis that SP are informative of Ultra Fast Charging, we find the following outcomes. In Achtnicht, Bülher et al. (2008) and Ziegler (2010) the marginal utility of refuelling is a constant and their models exhibit a very strong effect of this attribute with a WTP ranging from 200 to 300 €/% of refuelling stations providing the fuel corresponding to a given vehicle category. However, the assumption of a constant marginal WTP appears as a limitation of these results, while it is more than likely that the marginal utility of refuelling stations will be decreasing. For this reason, the approach by Greene (2001) can be preferred, where the utility of refuelling stations can be represented as an exponential function:

$$V_{ufc}(s) = Ce^{bs} \qquad \text{Eq. 4}$$

Where $V_{ufc}$ is the piecewise utility associated with the ultra-fast charging network, s is the share (fraction) of refuelling stations that offer fuel, b and C are behavioural parameters. The parameters C<0 and b<0 can be identified by assuming values for the benefit of recharging stations for s = 0 and for another appropriate value of s. This benefit is, analytically, equal to the ratio of the utility divided by the marginal utility of income (-$\beta_c$) in order to convert utility into money value[3]. Thus, one can write:

$$V_{ufc}(s) = -y_1\,\beta_c e^{\left(\ln\left(\frac{y_2}{y_1}\right)/x_2\right).s} \qquad \text{Eq. 5}$$

Based on evidences found in the literature and in particular (Achtnicht, 2010) as well as (Brownstone, Bunch et al., 2000), one can assume a penalty of 5000 € for a 0% refuelling stations ($y_1$=-5000), and 1000 € for 20% refuelling ($y_2$= -1000, $x_2$= 0,20) and thus obtain the following piecewise utility that can be included in the Synthetic Utility Function:

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[3] We can write : $V_{ufc}(0)/-\beta_c = y_1$ and $V_{ufc}(x_2)/-\beta_c = y_2$ .
$V_{ufc}(0)/-\beta_c = y_1$ implies C= $-y_1\beta_c$,.
$V_{ufc}(x_2)/-\beta_c = y_2$ implies b= $\ln(y_2/y_1)/x_2$,
Thus $V_{ufc} = -y_1\,\beta_c e^{\left(\ln\left(\frac{y_2}{y_1}\right)/x_2\right).s}$

$$V_{ufc} = 5000\beta_c e^{(\ln(0.2)/(0,2)).s} = 5000.\beta_c(0.2)^{(5.s)} \quad \text{Eq. 6}$$

### Car performance

Car performance can be expressed in terms of horsepower or acceleration time or maximum speed. All these features are linked based on engineering car design considerations. Available WTP's for HP range from 70€/HP (Axsen, Mountain et al., 2009) to 142 euro/HP in (Achtnicht, 2010). Based on some hedonic data that were collected on a set of car models sold on the German market, we would not recommend to use a WTP that is lower than the 50 €/HP revealed by market conditions. 70 €/HP appears, considering the few elements available, a reasonable estimate.

### Operating costs

Operating costs consists of fuel costs and maintenance costs. We first concentrate on fuel costs. A general finding of transport economics is that car purchasers consider fuel cost with an intertemporal discounting that is far higher than for other goods (Greene, 2010; Turrentine & Kurani, 2006). In order to verify the existence of such an effect in SP elicited preferences we performed a comparison of the value of fuel economy expressed in SP and the value it would have for a fully informed, consistently discounting, consumer. Details of this calculation, provided in appendix, suggest that SP based Willingness-To-Pay's for Fuel Economy imply a very strong discounting.

Elaborating on this information, one may exploit a remarkable pattern that appears in Table 2. Several authors (Axsen et al., 2009; Knockaert, 2005; Mabit & Fosgerau, 2011) find converging results in that operating costs are accounted for 4,2 to 4,9 years of expenses. This number, significantly lower than the lifetime of vehicles, expresses the strong discounting effect taking place in the valuation of operating costs. An average value of 4,5 years of expenses, an assumption that makes (perceived) fuel cost intrinsically dependent on mileage, provides a reasonable guidelines to estimate the impact of fuel cost on purchase behavior and can be proposed in the Synthetic Utility Function.

### Other costs

The logic implemented for fuel cost can be applied similarly to other maintenance costs. In the case of alternative fuel vehicles the relevant costs are:
- Road tax,
- Parking hire (for household without a private garage),

- Expected battery replacement costs.

The latest item of this list consists in non-recurrent costs, so it does not need to be treated as annual flows. Consistently with the 4,5 years rule, they can be discounted based on the rate (close to 16 %) that is implicit in the 4,5 years rule.

## Environmental features

Results of existing surveys are not highly conclusive and sometimes counter-intuitive (see for instance the positive sign of the coefficients associated with $CO_2$ emissions in Achtnicht (2010), while Ziegler (2010) obtains negative coefficients on the same data). Most of the available valuation results are expressed in % of an ICE car. Some results are close one another Batley, Toner et al., (2004), Brownstone, Bunch et al. (2000); Knockaert (2005) find around -80 € /% considering an average 150 g/km (that roughly summarizes emissions for European countries at the times the survey were made) we find a willingness to pay in the order of magnitude of -50 €/g. While these different estimates exhibit some consistency, we find some reasons not to include $CO_2$ emissions in the synthetic utility function. One reason is that $CO_2$ valuation could easily be contaminated by a so called warm-glow effect, where consumer express their adhesion to the general idea of reducing pollution through the questionnaire without that it really reflects their purchase behaviour. Additionally, in most countries, consumers were until recently little informed and potentially little concerned about the $CO_2$ emissions of their cars. As a consequence, our provisional recommendation is to make a conservative estimate of null WTP for $CO_2$ emissions.

## Alternative Specific Constants

Additional to attributes explicitly specified in the survey, one should allow for the fact that each technology may have some intrinsic or residual utility that is not reflected in the explicit attributes. Conform to the standard approach in Discrete Choice Modeling, these utilities can be represented by Alternative Specific Constants (ASC). Consider that Alternative Specific Constant for the different technologies are net of other attributes. This implies that their value should generally decline with the introduction of additional attributes. Strange enough, the Alternative Specific Constants exhibit contradictory values when compared across studies. Achtnicht (2009, 2010) find WTP values in the order of magnitude of 5 000 to 20 000€. The discrepancy in the results can be related to the idiosyncrasies of each survey and the limited number of attributes that can be introduced in a single SP survey. Note for instance that the large values obtained in Ecocars project surveys for the various

Alternative Specific Constants (Achtnicht, 2009, 2010) may relate to the absence of the range attribute in the conjoint analysis.

Values for the Alternative Specific Constants result from the attributes that are not included in the utility function. In the case of the proposed Synthetic Utility Function, the (virtually infinite) list could contain:
- luggage room,
- number of seats,
- availability of maintenance network,
- environmental friendliness,
- image,
- nationality of car manufacturers,
- maintenance network,
- uncertainty of maintenance costs,
- perception on how much the technology is likely to survive in the future,
- resale value,
- safety.

## Diversity

Additional to car attributes, one may also consider the notion of diversity in each technology supply. The value of (the lack of) diversity for certain technologies can be a hindrance to market penetration. The basic idea behind this analysis is that if certain models are not available for certain technologies the consumer will change technology rather than model.

In MMEM model, diversity was eventually not included in the Synthetic Utility Function. This relates to the fact that some elements of Bass diffusion approach have been subsequently added. Thus including these features together with diversity attribute would have been redundant and would have given excessive limitations to newer technologies. We however provide a brief discussion of diversity for sake of completeness.

Inclusion of diversity in a choice model has been thoroughly investigated in TAFV and AVID models (Greene, 2001; Leiby & Rubin, 1996, 2000; Santini & Vyas, 2005). It is also present in model estimates by (Brownstone et al., 2000) who find a Willingness-To-Pay of 7300 to 8000 $ per a unit increase of the logarithm of the number of models available for a given technology. The attribute log(models) ranges from 0 to 3,6 (mean value 0,72). This suggests that the maximum difference in the cost of the lack of diversity could be as high as 28,8 thousand dollars. While the difference between the average value and the minimum value would be close to 5 thousand dollars.

In the approach proposed by (Greene, 2001), the value of diversity is expressed by the following formula:

$$\text{Value of diversity} = (a/-\beta_c).\ln(n_i/N) \qquad \text{Eq. 7}$$

With

$\beta_c$     coefficient of cost in the utility function

$n_i$     is the number of vehicle types offered by technology i

N     is the number of vehicles types offered by the conventional technologies (the maximum number of vehicles types among different technologies).

a     is a parameter that reflects the order of introduction of vehicles in the new technologies.

a = 1 would reflect a random order of introduction,

a = 0.37 corresponds to market conditions observed by (Greene, 2001).

To our best knowledge, we are not aware of any other study that provides alternative values for the *a* parameter. Thus, the piecewise utility of diversity is obtained by multiplication of the previous equation[4] by the marginal utility of money $-\beta_c$:

$$U_d = 0.37.\ln(n_i/N) \qquad \text{Eq. 8}$$

To conclude, if the limited variety of models available for consumer is not included in the forecast model, there is a risk to overestimate the sales of innovative technologies. Unless the model contains some features specifically designed to replicate diffusion phenomenon (in the case of MMEM simulation tool, this was made by reintroducing some Bass diffusion mechanisms downstream the application of the Discrete Choice Model), one needs to introduce diversity in the utility function and this can be done whether using the approach provided by Greene or calibrating a willingness to pay function based on SP data. Regarding the very latest possibility one can probably hope that more information will be made available in the next future in order to be in conditions to provide sound estimates.

In the previous section, we have proposed parameter values and functional form of a Synthetic Utility Function suitable for German market and fairly adaptable to other (typically: European) markets. A synoptic of the Synthetic Utility is provided in appendix 1. While this specification can be helpful to incorporate existing evidences about attribute valuation, it is temporary, as it is aimed, by nature, to be updated when other results become available in the future.

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[4] Note that this formula is valid even when applied to segmented data (for instance only Mittelklasse segment) due to the ratio $n_i/N$ that is meaningful also on a segment of the market.

# Conclusion

In this article, we have investigated the use of SP surveys to forecast the diffusion of electric and Alternative fuel vehicles.

As far as methods are concerned, we identified a number of advantages of SP surveys compared with alternative methods: T.C.O. calculation and diffusion theory, identifying as main benefits of SP the possibility to make the diffusion attribute (and thus policy) responsive.

As far as existing surveys are concerned, we advocate the view that, parallel to the accumulation of extra survey results, efforts should be dedicated by the community of transport scientists on the consolidation of existing outcomes into synthetic results. Based on this principle, we propose a set of Willingness to Pay that, to our view, corresponds to the market conditions prevailing on the German car market at the present time and, provided sufficient care is taken in considering specific local conditions, can be transferred to a number of other contexts.

Eventually, going beyond the state of the art we see two questions that are important for the use of SP surveys in market penetration forecasting.

First the question of consumer heterogeneity has been touched only marginally in this article. This does not mean that it is found unimportant. In MMEM model, garage ownership was introduced as a socio-economic variable in the choice model, but arguably many other aspects could be taken into account to represent heterogeneity. Multinomial logit allows for stochastic variation of utility that, in the MNL tradition was seen as a way to introduce heterogeneity in the choice process. Introducing more advanced techniques from the family of Kernel logit, for the representation of heterogeneity would be a more satisfactory option, but our meta-analysis suggests that too few results are available in the literature at this stage to provide consolidated results for implementation. Another way of introducing heterogeneity would be to rely on a larger number of socio-economic characteristics or variables influencing car purchase decision. Our analysis suggests that while various socio economic features were introduced in existing models, some aspects of car purchase decision that are arguably important (see for instance first car vs. second car) still have very little applications.

A second question relates to how SP surveys results should be interfaced with some (typically Bass) diffusion mechanisms. The nature of the behavioural mechanisms elicited in SP survey is controversial. Should they be considered as expressing the

current preferences of car purchasers, or a potential that is not limited by currently available information and habit. Both of these views can be supported by solid arguments, but they lead to very different uses of SP surveys. In one situation SP derived market shares can be used directly as market penetration forecast, in the other they just constitute a potential that will be reached only progressively. While these two ways of dealing with SP surveys provide highly different outcomes, this question has only received limited attention in applied economics literature and probably deserves to be ranked high on the research agenda.

## Appendix

### Appendix 1 – Components of the Synthetic Utility Function

| Category | Attribute (unit) | Piecewise utility |
|---|---|---|
| Autonomy | Range (km) | $-\beta_c * 103\ 522\ €* Range^{0,27}$ |
| | Ultra fast charging (fraction) | $5000.\beta_c (0.2)^{(5.s)}$ |
| Performance | HP | $-\beta_c *50*HP$ |
| Fuel Costs | Fuel costs | $\beta_c *(4,5\ yrs\ of\ fuel\ cost)$ |
| Recurrent maintenance costs | Road tax, Mechanical maintenance | $\beta_c *(4,5\ yrs\ of\ cost)$ |
| Non recurrent costs | Purchase costs € | $\beta_c.\ purchase\ cost$ |
| | Other investment cost (e.g.: wall socket) | $\beta_c.cost$ |
| | Expected Battery replacement costs | $(1/1+i)^n.\beta_c.cost$ |
| Environmental Friendliness | $CO_2$ emissions | 0 |

Note: $\beta_c = -0,0003$, i=16 %, n = number of years ahead where battery replacement may take place.


### Appendix 2 - Willingness to pay for fast charging

Fast Charging is valuable for consumers only as far as Ultra Fast Charging is not largely deployed. In other words, the more Ultra Fast Charging is available, the smaller the marginal utility of Fast Charging. This suggests a utility of Fast Charging stations that is impacted by some "attenuation function" representing the impact of Ultra Fast Charging, such as represented on Figure 3.

**Figure 3 - Willingness to pay for fast charging stations**



**Figure 3 - Willingness to pay for fast charging stations**
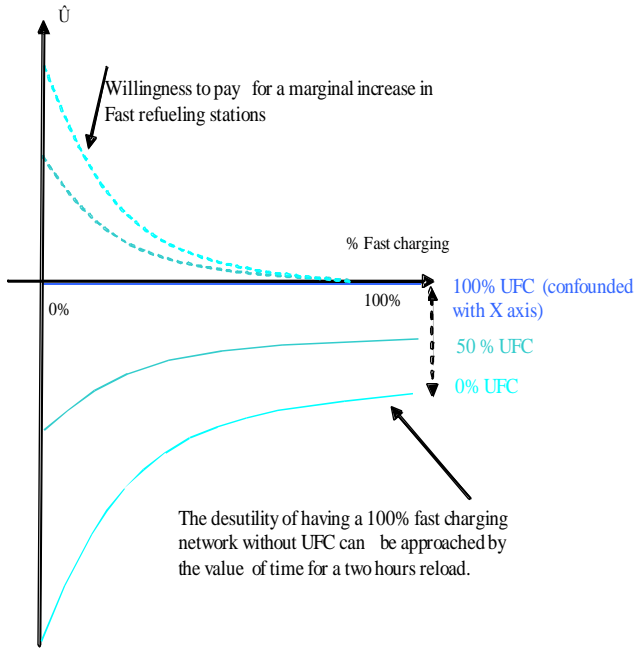
A tractable solution could be as followed

$$V_{fc} = \left(C_{fc}e^{b_{fc}s_{fc}} + \tau\right)\left(1 - s_{ufc}\right) \qquad \text{Eq. 9}$$

where: $V_{fc}$ is the utility of Fast Charging stations, $C_{fc}$ and $b_{fc}$ are behavioural coefficients, $s_{fc}$ is the share of refuelling stations offering Fast Charging, $s_{ufc}$ share of refuelling stations with Ultra Fast Charging and $\tau$ is a penalty for charging time

In the above equations, $C_{fc}$ and $b_{fc}$ can be estimated by using the values obtained for Ultra-Fast Charging (this corresponds to the simplified assumption that all the difference in fast and ultra-fast is due to the value of time lost in refueling operations).

Regarding $\tau$, one can suggest:

$$\tau = \beta_c .20 \text{ € x number of fast refuelling operations} \qquad \text{Eq. 10}$$

$$\tau = \beta_c \ 20 \text{ € x (lifetimekm/0.8 x range x fraction of fast refuelling) Eq. 11}$$

The 20€ value, a speculative one we guess, is based on two hours refuelling time valued at 10 €/h, a value slightly lower than the value of time used in transport evaluation and reflecting the fact that, in a fraction of the refuelling occasions, the users will be in conditions to make some use of their time while reloading. The 0.8 coefficient is provided as a provision reflecting the fact that refuelling operations will not deal with the full battery available

capacity. The latest term: fraction of fast refuelling is probably the most speculative and its determination goes beyond the scope of the present article.

## Appendix 3 - Comparison of SP survey fuel cost and fully informed, consistently discounting economic behaviour

Economic analysis has suggested that the perception of fuel economy by car purchasers can be highly distorted (Greene, 2010). In the present appendix, we compare two types of calculation: Present value of fuel costs and SP based WTP. In this comparison, a "rational" discounting consumer will consider fuel consumptions costs as follows:

$$PVFC = \sum_{i=0}^{L} \frac{p.(k/100).c}{(1+\delta)^i}$$
Eq. 12

Where PVFC is the Present Value of Fuel Cost (€), k is the annual kilometrage (km/years), p fuel price (€/l.), c consumption (l/100km), $\delta$ discounting rate, L Lifetime (years). When considering an alternative car with different consumption $c'$, and/or different fuel price $p'$, the change in consumer present fuel cost will be:

$$\Delta PVFC = \sum_{i=0}^{L} \frac{p.(k/100).c}{(1+\delta)^i} - \sum_{i=0}^{L} \frac{p'.(k/100).c'}{(1+\delta)^i} = (cp - c'p').(k/100)\sum_{i=0}^{L} \frac{1}{(1+\delta)^i}$$
Eq. 13

It is possible to calculate the benefit of a unit cost reduction by computing $\Delta PVFC$ for (cp-c'p')=1. The alternative would be to compute the benefit for a reduction of fuel consumption in physical terms, but this alternative creates some computational complications[5]. If we represent on one single graph $\Delta PVFC$ as a function of kilometrage for a given discount rate (4, 6 and 8% in our case), we can compare the outcome of rational discounting logic with WTP as expressed in SP surveys.

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[5] The impact of an increase of consumption by one l/100km found by calculating DPVFC for (c-c')=1. But this calculation is cumbersome when the simplifying assumption that p=p' cannot be made. Thus there is a limitation in considering willingness to pay for a liter reduction in fuel consumption, just because the cost of a liter is not the same across fuel alternatives.

**Figure 4 : Present value of fuel cost reduction of 1€/100km (comparison of SP survey with "count and discount" consumer)**
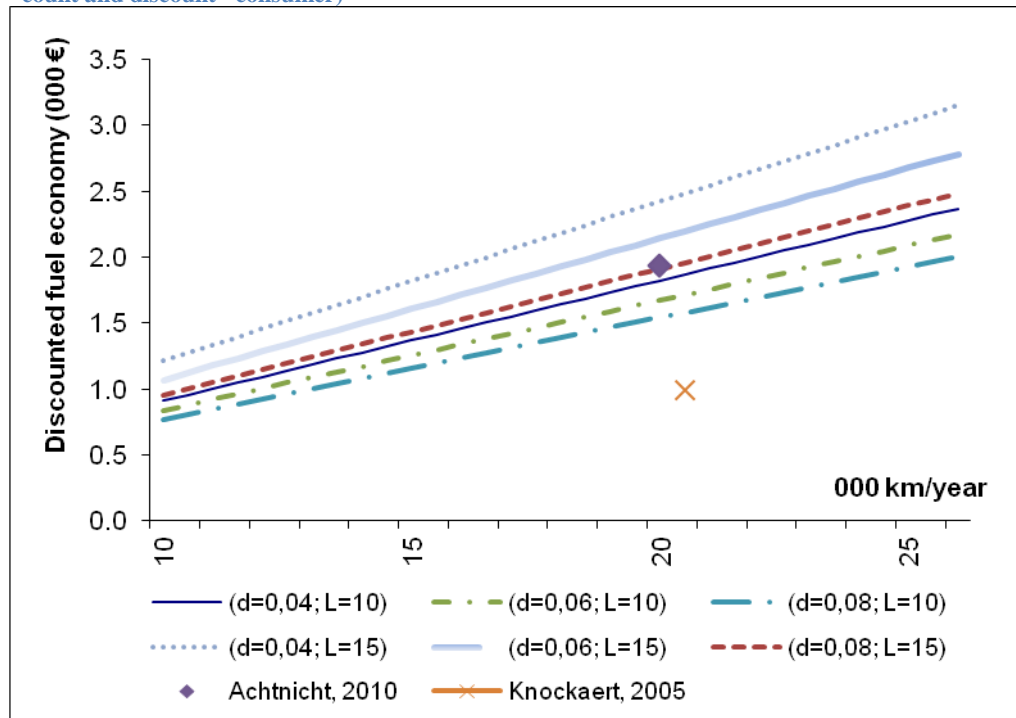


Note: considers three discount rate assumptions
(4%,6%,8%) and two vehicle lifetime (10 and 15 years).

If WTP based on Stated Preferences would exactly reflect the (discount rate and car lifetime dependent) computation of discounted value of fuel economy, the curves on Figure 4 would intersect the points representing WTP at the average km (Figure 4 reports such results for Achtnicht (2010) and Knoackert (2005)[6]). Reasons for deviations can be due, apart from statistical inference issues, to a different discount rate, lifetime duration or adherence to other types of rationality by the consumer.

   The two point data we use to make a comparison provide a mild conclusion with Achtnicht observation compatible with an 8 % discount rate and 15 years lifetime and 4% discount and 10 years; Knoackert providing lower values (compatible with a discount rate slightly higher than 8, or a shorter lifetime).

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[6] The average kilometrage per year for Knoeckaert is 20206 km that do not actually represent sample average but some supplementary data (see Knockaert, 2005, p 14.)

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