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# Bass Re-visited: Quantifying Multi-Finality

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**ABSTRACT**

As forecasting the diffusion of new technologies results in unreliable predictions when only few trend data are available, scholars and practitioners alike favor foresight efforts of a more qualitative nature to gauge foreseeable futures. We argue that it is feasible to reconcile (quantitative) forecasting models with (qualitative) scenario development efforts by advancing a set of heuristics building on known diffusion curves. Rather than focusing on the ultimate set of parameter estimates, we explore a multi-dimensional space consisting of a wide range of values for each parameter implied. We demonstrate this approach for Battery Electric Vehicles in Europe and the US. Resulting outcomes are assessed in terms of how well they explain current observations by means of a loss function. The loss function allows us to evaluate the presence of different end states (multi-finality), their frequency of occurrence, and the implied time frames. The insights obtained inform foresight exercises in a number of distinctive ways. First, it becomes feasible to qualify the likelihood of - and the time horizon implied by - different scenarios. Second, allowing for multiple pathways and end states directs our attention to the antecedents required for different scenarios to unfold, which can inspire *backcasting* efforts of a more qualitative nature. Finally, applying the advanced logic on more fine-grained levels of analysis allows assessing the (differential) impact of policies oriented towards stimulating diffusion. As such, quantitative heuristics become a complement to scenario development exercises, rather than an inferior or even neglected substitute.

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## Bass Re-visited: Quantifying Multi-Finality

### 1. Introduction: from forecast to foresight (and back)

"Forecasts are nothing, forecasting is everything"[1]

Since the seminal work of Rogers (1962), models depicting the diffusion of an innovation have been proposed and explained in various research disciplines. Rogers (1962) defines the diffusion of an innovation as a social process by which an innovation becomes adopted within a community of users. In the marketing and communication tradition, the diffusion of an innovation represents the process of market adoption of new products and services driven by social influences, taking into account interdependencies among consumers as well as various market players (e.g. Mahajan et al., 1990; Peres et al., 2010). Likewise, management and economic scholars focusing on innovation define and model the diffusion as the extent to which an innovation becomes adopted within and across social groups over time (e.g. Brown, 1981; Stoneman, 2002).

The main models in diffusion literature suggest that growth patterns of innovations follow sigmoid growth curves. The logistic equation (Verhulst, 1838, 1845; Pearl and Reed, 1920; Lotka, 1925), the Gompertz model, and the Bass model are commonly used mathematical representations of these S-shaped curves[2]. All these models involve an estimation of at least three parameters, related to the takeoff and steepness of the curve as well as its saturation level. The simple logistic equation – initiated by Verhulst (1838, 1845) – can be written as

[1] The original quotation from D. Eisenhower pertains to planning ("Plans are nothing, planning is everything.")

[2] A wider range of models has been explored in the literature; for a concise overview covering 29 different model specifications, see Meade and Islam (1998).

$$X_{t=} \; = \frac{a}{1 + c^{-bt}} \,,$$

whereas the Gompertz model equals

$$X_t = a^{-c^{-bt}}$$

Where:

$X_t$ = the cumulative number of adopters at time t,

a = the saturation level,

b and c = entry (growth) and exit (displacement) rates.

In this contribution, we focus on the diffusion model advanced by Bass (1969). The Bass model has been widely adopted in marketing and innovation studies alike (e.g. Mahajan et al., 1990; Chandrasekaran and Tellis, 2007; Massiani and Gohs, 2015) due to its straightforward intuition – the model reflects the social dynamics implied – as well as its predictive ability (for an overview, see e.g., Parker, 1994; Chandrasekaran and Tellis, 2007). In terms of adoption, the Bass model distinguishes innovators from imitators, with both groups reflecting a distinctive behavioral rationale and being influenced by different means of communication (see Bass, 1969; Lekvall and Wahlbin, 1973; Mahajan et al., 1990; Bass, Krishnan, and Jain, 1994).

The basic premise underlying the Bass model is that the probability that an individual purchase will be made at time t given that no purchase has yet been made is a linear function of the number of previous buyers. Thus:

$$\frac{f(t)}{1 - F(t)} = p + \; q \;[F(t)]$$

Where:

f(t) = the proportion of the market potential that adopts at time t (i.e., density function),

F(t) = the cumulative proportion of the market potential that has adopted by time t,

p = coefficient of innovation (i.e., innovation rate) and,

q = coefficient of imitation (i.e., imitation rate).

If m represents the ultimate number of adopters, the number of adopters at time t can be expressed as mf(t) = n(t) and the cumulative number of adopters at (including) time t will be mF(t) = N(t). The continuous equation above could then further be written in its discrete form as:

$$N_t = N_{t-1} + p(m - N_{t-1}) + q\frac{N_{t-1}}{m}(m - N_{t-1})$$

Where:

$N_t$ = the cumulative number of adopters at time t

m = the potential market (the ultimate number of adopters),

$(m - N_{t-1})$ = non-adopters at the beginning of period t

$(N_{t-1} / m)$ = the fraction that has already adopted

In principle, only three observations would be sufficient to delineate the three parameters p, q and m (as illustrated in Bass, 1969, p. 224). At the same time, estimations become more complicated as soon as more data points become available because stochastic variability will be rule rather than exception (Modis and Debecker, 1992). In his seminal work, Bass (1969) used ordinary least squares (OLS) on discrete time series to distill a final model.

Schmittlein and Mahajan (1982) address a number of shortcomings of the OLS approach and introduce a procedure based on maximum likelihood estimation, while Srinivasan and Mason (1986) introduce a non-linear least squares approach (NLS). Both techniques estimate the parameters directly from the differential equation of the diffusion model and yield an improvement in predictive validity. However, both approaches require an initial value for each parameter (which could be provided by the initial OLS estimates, thus introducing a two-step method to estimate parameters; see also Srinivasan and Mason, 1986).

In addition, several authors modified and refined the Bass model by introducing additional parameters – for example, incorporating marketing variables, the discovery of new uses, the impact of pricing strategies, the growth of relevant infrastructure, as well as the entry of competition (Urban et al., 1996); by considering different stages of diffusion in different countries, and by incorporating the diffusion across successive generations of technology (for an overview, see e.g., Mahajan et al., 1990; Parker, 1994; Meade and Islam, 2006). Whereas such refinements seem appropriate, the findings of Bass, Krishnan, and Jain (1994) reveal that the *simple* Bass model fits sales almost as well as the more complex models that sought to correct for its limitations.

At the same time – and despite several refinements in parameter estimation techniques – they all remain 'problematic' in terms of forecasting 'the' future as model estimations result in unstable and rudimentary predictions when only few 'trend' data are available (i.e., during the early stages of diffusion). More specifically, parameter estimations lack predictive validity when the initial data set (used to gauge parameter estimates) only contains pre-takeoff sales since models require data at both inflexion points (takeoff and slowdown) in order to become 'predictive' in a precise and valid manner (Heeler and Hustad, 1980; Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986; Mahajan et al., 1990; Venkatesan and Kumar, 2002; Chandrasekaran and Tellis, 2007). Stated otherwise, diffusion models tend to yield only accurate insights retrospectively. Bass (1969) already indicated that parameter estimates are very sensitive to small stochastic variations when there are only a few data points available, whereas Heeler and Hustad (1980) suggest that stable and robust parameter estimates can be obtained only if the data under consideration (i) contain at least ten observations; and (ii) include the peak of the non-cumulative adoption curve. Similar concerns have been repeatedly expressed ever since (e.g., Srinivasan and Mason (1986), Mahajan et al., 1990; Venkatesan et al., 2004; Becker et al., 2009; Gross, 2008; Davidson et al., 2013). In their application of the NLS estimation method, Van den Bulte and Lilien (1997, p. 350) concluded that "expecting a simple time series with a handful of noisy data points to foretell both the ultimate market size and the time path of market evolution is asking too much of too little data", whereas Mahajan et. al (1990, p.9) conclude that "[…] parameter estimation for diffusion models is primarily of historical interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes".

In this contribution, we present the argument for and demonstrate how quantitative forecasting models could inform qualitative scenario development efforts even in situations where only relatively short time series are available (i.e., during the pre-takeoff phase of the diffusion process). Rather than using Bass's model as a starting point to derive the 'optimal' set of parameter values, we design heuristics that start from the premise of multi-finality. Multi-finality has been described in physics and system theory as the phenomenon that "similar initial conditions may lead to dissimilar end-states" (Buckley, 1967). The heuristics implied revolve around the development of a three-dimensional search space (reflecting the presence of three model parameters to be estimated) and the introduction of a loss function to assess the 'goodness of fit' of potential outcomes with current observations. Combined, this approach allows us to derive multiple, plausible diffusion pathways reflecting a wide range of values for each parameter. Given this design approach and the possibility to apply it even when only relatively short time series are available, it is also deemed relevant and fit for use when important exogenous shocks are applied to the system that is examined and modeled. Hence, incorporating the multi-finality logic replaces the quest for the most accurate estimation by a systematic assessment of plausible trajectories based on limited time series intrinsic to the early stage of the diffusion process and applicable along a case or system spectrum ranging from instances of endogenous continuity to exogenous discontinuity.

By assessing possible diffusion pathways for Battery Electric Vehicles in Europe and the United States (for the time period 2011-2017), we demonstrate that the proposed heuristics can inform qualitative foresight exercises in a number of distinctive ways. As multiple pathways are qualified ex ante and simultaneously, the presence of different end states with their corresponding frequency of occurrence can be considered as a starting point to quantify Knightian uncertainty (Knight, 1921)[3]. This quantification yields insights into the time horizon of the different scenarios, but it also directs our attention to the antecedents required for *backcasting* the different unfolding scenarios. Here, the advanced grid logic and the implied heuristics can be highly informative.

[3] "'*Uncertainty*' must be taken in a sense radically distinct from the familiar notion of '*risk'*, from which it has never been properly separated. […] The essential fact is that '*risk'* means in some cases a quantity susceptible of measurement […] It will appear that a measurable '*uncertainty'*, or '*risk'* proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an '*uncertainty'* at all."

Indeed, when introducing more fine-grained levels of analysis (e.g., countries, states, and regions), it becomes feasible to assess the impact of different characteristics of local innovation systems (including policies) on the diffusion process of the underlying technology (product). Such insights can inform appropriate action so that diffusion dynamics are influenced in the direction of the desired end states.

The paper proceeds as follows: Section 2 outlines the data and the heuristics deployed. In Section 3, the major results obtained for the diffusion of the Battery Electrical Vehicle (for Europe and the US) are presented. We conclude by discussing the relevance and limitations of the heuristics advanced in Section 4.

## 2. Data and heuristics

The heuristics deployed to assess multi-finality will be illustrated by means of data reflecting the recent adoption of Battery Electric Vehicles (BEVs). While electrical cars per se are not a novel technology (or product)[4], the entrance of Tesla in the car manufacturing industry and especially the introduction of the model S (2012) has created a new impetus resulting in expectations that mass adoption of BEVs is at hand. Current outlooks (e.g., The Economist, 2017; BloombergNEF, 2019) suggest a massive adoption of BEVs, approaching a global market share of 25 percent by 2030.

[4] Note that the first electric road vehicles were already constructed in the 1880s, with G. Trouvé, W. Ayrton, J. Perry and F. Kimball amongst these pioneers. In 1899, C. Jenatzy captured the world road speed record with his 'Jamais Content'. One of the most eccentric and interesting manufacturers of early electric cars was Oliver P. Fritchle. He sold his first vehicle in 1906 and built about 198 vehicles per year between 1909 and 1914. (https://www.curbed.com/2017/9/22/16346892/electric-car-history-fritchle)

### *2.1 The car market – facts and figures*

Modelling the growth dynamics of new products involves a distinction between stocks (the installed product base) and flows (the inflow/replacement of/by new products) (see Sternman, 2011). In Europe (EU-28), the stock of cars in 2016 equaled 259.7 million, with 15 million new annual registrations. In 2016, the average age of the EU fleet was 11 years. At this pace of replacement, it would take more than 17 years before the European fleet is renewed. If prospective new vehicle buyers consider purchasing an *electric* model but desist at the moment of truth, it takes – mutatis mutandis – more than 17 years before the 'old' technology exits the European fleet. The US market comprised 269 million motor vehicles in 2016, including passenger cars, motorcycles, (light) trucks, busses and other vehicles. The US market is characterized by a demand shift from automobiles to larger vehicles such as light trucks. In 2016, there were almost 113 million automobiles registered in the United States with an average age of 11.6 years. In 2017, 6.3 million new automobiles were registered. In this exercise, we focus on the data concerning automobiles for which – at this pace of replacement – almost 18 years would pass before renewal. Table 1 summarizes some key figures concerning the European and US fleets:

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Insert Table 1 about here

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Although the Battery Electric Vehicle is still situated in the early, pre-takeoff phase of market adoption, time series with seven years of sales data are available for Europe[5] and the US (2011 to

[5] In Europe, one additional observation for the BEV stock per 2010 is also available (i.e., stock of 734 BEVs). However, we opt to omit this *first* observation, since the corresponding data is not available for the US market while the BEV models turned out to be simultaneously available in both regions. Thus, we will continue with a symmetric dataset for both regions.

2017). Table 2 reports the cumulative actual sales data (i.e., stock) of Battery Electric Vehicles in both regions.

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Insert Table 2 about here

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For both regions, we note that the adoption is characterized by steady growth; however, sales are not (yet) doubling annually. Although data for 2018 are currently available, we deliberately exclude these from the simulations because this will allow us to assess the predictive validity of the patterns obtained, at least in the short term (see Section 4).

### *2.2 Modelling diffusion pathways: implied heuristics*

With basic figures on the total automotive markets in Europe and the United States, and yearly sales data of Battery Electric Vehicles over the last seven years, we can model diffusion pathways. Table 3 summarizes the heuristics deployed, which will be clarified and illustrated in this section.

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Insert Table 3 about here

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We focus on the first-purchase diffusion models as advanced by Bass (1969). We assume that, in this early stage, the available sales data as depicted in Table 2 equal the first adoptions (Parker, 1994), so no adjustments are made for replacement sales in this exercise. This is consistent with the average age and renewal periods from Table 1. Starting from the initial Bass model, we develop an exhaustive, three-dimensional search space reflecting plausible diffusion pathways for BEV.

The search grid consists of 500,000 different combinations of the implied parameters m, p and q for each region (EU and US). For m, we allow variations of 10 percent (from 10 to 100 percent of market share) while, for p and q, the ranges vary with 250 and 200 steps respectively:

- $10\% \leq m \leq 100\%$ (10 steps of 10%)
- $0.00001 \leq p \leq 0.00250$ (250 steps of 0.0001)
- $0.01 \leq q \leq 2.00$ (200 steps of 0.01)

The ranges of both parameters (p and q) are chosen so as to reflect the variety (of parameter values) observed in the current literature, as summarized by Massiani and Gohs (2015) for electric cars.

The exhaustive search grid allows us to assess all different combinations of the three parameters, with no ex ante assumption on either initial values for each parameter or potential equivalences between different value combination across the three parameters. Thus, in the first step, all imaginable combinations are considered to gauge potential diffusion pathways.

In a next step, we select more plausible diffusion paths by introducing a loss function. This loss function assesses how well each parameter combination explains the available observations. In this case, we use the figures reported in Table 2 as observed data (separately for Europe and for the US) and compare them systematically with the predicted values obtained from each parameter combination. In total, we calculate one million loss functions (two times 500,000) whereby the 'goodness of fit' for each combination is defined and calculated as:

$$R^2 = 1 - \frac{SS\ Error}{SS\ Observed}$$

In a final step, we introduce a threshold value pertaining to the $R^2$, in order to select – and, in a subsequent step, to assess and qualify – more plausible scenarios. For this paper, we chose to select all parameter combinations that pass the 99 percent threshold[6.]

These diffusion paths (with an $R^2 > 0.99$) are labelled as the *more likely* scenarios because these models are best at explaining what we can currently observe in terms of market adoption. We obtain 689 models[7] for Europe and 1,864 models for the US that meet this requirement. Figures 1a and 1b compare the actual observations (i.e., the red dotted line) with the selected *more likely* scenarios (due to graphical limitations, only those models exceeding the 99.65 percent threshold are depicted) for both Europe (Figure 1a) and the US (Figure 1b).

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Insert Figures 1a and 1b about here.

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## 3. Selected diffusion pathways: how do they inform the future?

The heuristics implied derive plausible diffusion pathways that allow for the presence of multi-finality. Multi-finality implies that "similar initial conditions may lead to dissimilar end-states"

[6] Applying a threshold value of 95 percent, yields similar results as the ones reported here.
[7] Including the observation for 2010 in the European situation would lower this number to 321 *more likely* scenarios, which makes sense intuitively because this would impose the curve that fits with the extra observation point as well.

(Buckley, 1967), as visualized in Figures 2a and 2b (due to graphical limitations, we only depict those exceeding an $R^2 > 99.65$ percent[8]).

Incorporating the multi-finality logic replaces the quest for the most accurate estimation by a systematic and exhaustive assessment of plausible trajectories, based on the limited time series inherent in early stage data. Note that our results signal scenarios in which the electric car obtains a lion's share of the market. These scenarios are present in the subset of *more likely* scenarios but to a much lesser extent than scenarios closer to market share of 20 percent and lower, which becomes apparent when inspecting Table 4.

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Insert Figures 2a and 2b about here.

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Indeed, when different combinations of parameter values perform equally well in terms of modelling a current trend, the mere calculation and inspection of the resulting curves and their underlying parameter combinations enable us to assess the nature of different pathways to the future and to gauge their corresponding likelihood. Table 4 reports the market share distribution of the *more likely* scenarios for both regions, and it reveals that models closer to a market share of 20 percent and lower are much more present in the sample of *more likely* scenarios than scenarios that suggest a lion share for BEVs (market share of 50 percent and higher). The strong resemblance in terms of obtained frequencies per market share conditions between Europe and the US should be noted accordingly.

[8] The observed patterns are insensitive to the exact value of the threshold at least when this range is situated in the range between 95 and 99%.

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Insert Table 4 about here

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Finally, Tables 5a and 5b include some key figures for these *more likely* scenarios, on a yearly basis up to 2020 and with a five-year interval thereafter. Columns 2 to 4 provide the minimum, maximum and average market share of Battery EVs for this set of *more likely* scenarios. In 2025, the average ‘predicted’ values remain below 5 percent, both for Europe and the United States. In the most ‘extreme’ model, 5.80 percent (resp. 9.50 percent) of the European (resp. American) stock will consist of BEVs. In order to reach these scenarios, 37.55 percent (resp. 54.16 percent) of the new registrations (columns 5 to 10) should be composed of BEVs in Europe (resp. United States). Therefore, these findings contrast with some of the scenarios advanced by industry and/or policy makers projecting a global market share for electrical cars in excess of 10 percent by 2025 (The Economist, 2017; BloombergNEF, 2019).

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Insert Tables 5a and 5b about here

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## 4. Discussion and conclusion.

In this contribution, we advance heuristics which allow to assess the likelihood of different diffusion paths to unfold when only limited time series (on the adoption/diffusion) are available. The heuristics start from a sigmoid curve, assess a wide range of parameters simultaneously, and imply a loss function which qualifies the different parameter values in terms of ‘fit’ with respect to available observations. We illustrate the relevance of this approach by modelling the diffusion of the battery electrical vehicle. We demonstrate that engaging in quantitative modelling is a complement rather than a substitute for scenario development, and we argue that these heuristics could well inspire scholars to re-consider the relevance of forecasting models to scenario development for a number of reasons.

First, rather than searching for a unique – 'ultimate predictive' – set of parameter estimates for the Bass model, we consider different combinations of the underlying parameters ex-ante, simultaneously and (rather) exhaustively. By examining an exhaustive *range* of parameter values, the considered grid allows for multi-finality to unfold.

Second, the implied multi-finality seems to offer the potential to assess and model uncertainty (Knight, 1921) *within a technological trajectory* in a quantitative manner. If one accepts the idea that the occurrence of certain parameter values – within the subset of more likely scenarios – reflects the likelihood of unfolding, it becomes feasible to assess the likelihood as well as the time horizon inferred for all different scenarios. When different combinations of parameter values perform equally well in terms of modelling a current trend, the mere calculation and inspection of the resulting curves enables us not only to assess the nature of different pathways to the future but also to assess their likelihood.

Third, it becomes feasible to assess the time horizon for unfolding a technological trajectory. The scenarios that industry and policy makers are explicating in their diffusion projections (e.g., The Economist, 2017; BloombergNEF, 2019) seem optimistic. Instead, our models suggest in the 'short' term (6 years), an evolution towards a BEV market share – on average – ranging between

2.25 and 4.09 percent as more likely[9]. Notwithstanding the implied multi-finality in the long term, pathways pass through a narrow funnel (as visualized in Figures 2a and 2b) in the short term. In this respect, forecasting the market adoption in the short term becomes feasible even in situations where only relatively short time series are available.

Finally, the presence of multiple trajectories towards the future directs our attention to the antecedents required in *backcasting* the different scenarios to unfold (Robinson, 1982, 1990). Influencing these pathways towards more desired (higher) end stages might be achieved by introducing specific policies and measurements (e.g. providing financial (dis-) incentives to offset the substantial investment in acquiring a BEV) and/or to further invest in technological *breakthroughs* (on the level of cars, batteries), which might result in competitive price/value ratios. It should be noted that, in this respect, the proposed heuristics are instrumental as well. If different regions (or states, nations) opt for different policies and/or different technological platforms, one can start to model the differential impact thereof and assess whether, to what extent, and when different end states become attainable.

We want to end this paper by pointing out some limitations, which equal interesting avenues for future research. As we consider only one diffusion model, it would be relevant to introduce and extend the heuristics with diffusion patterns displaying more complex forms (e.g. Schmoch (2007), Meade and Islam (1998)). Likewise, validation of relevant parameter ranges, including potential trade-offs might be a concern to address, since it will influence the completeness of the search

[9] In this respect it is interesting to note that the real sales figures for Europe in 2018 equaled 150 003; our models for Europe (including also data for 2010) advanced a forecast of 152 700 (99,1% accuracy).

space taken into consideration. Finally, while we claim to have found a way of quantifying Knightian uncertainty, it goes without saying that this is only partly true: the development of a certain technology-product platform is considered in isolation (in this case the Li-Ion Battery Electrical Vehicle). Complementary and competing developments beyond this platform could equally start to influence the growth (or decline) dynamics of this trajectory. Therefore, heuristics that include a more systemic perspective would seem to be a logical next step; including the incorporation, modelling and impact assessment of policies. We hope our contribution will inspire colleagues and scholars to engage in such efforts.

## References


Bass, F.M, Krishnan, T.Y., and Jain, D.C. (1994). Why the Bass model fits without decision variables. *Marketing Science*, 13 (3), 203-223.

Bass, F.M. (1969). A New Product Growth for Model Consumer Durables. *Management Science*, 15 (5), 215-227.

Becker, T.A., Siduh, I., and Tenderich, B. (2009). *Electric vehicles in the United States a new model with forecasts to 2030*. Berkeley: University of California.

BloombergNEF (2019). Electric Vehicle Outlook 2019.

Brown, L. (1981). *Innovation Diffusion: A New Perspective.* London: Methuen.

Buckley, W. (1967) Sociology and Modern Systems Theory. *Prentice-Hall, Englewood Cliffs.*

Cao, X. (2004). The future demand for alternative fuel passenger vehicles: a diffusion of innovation approach.

Chandrasekaran, D., and Tellis, G. J. (2007). A critical review of marketing research on diffusion of new products. In: N. K. Malhorta (Ed.), *Review of Marketing Research,* 39-80. Armonk, NY: M. E. Sharpe.

Davidson, M., Cross-Call, D. Craig, M., and Bharatkumar, A. (2013). Assessing options for accommodating electric vehicles in Santa Delano Valley. *USAEE Case Competition 2013. T. T. a. P. Group: 49.*

Gross, U. (2008) Prognose des Absatzmarktes für alternative Antriebe – Modellbildung und Simulation. *Universität Karlsruhe* (TH): 174.

Heeler, R.M., and Hustad, T.P. (1980). Problems in predicting new product growth for consumer durables. *Management Science*, 26 (10), 1007-1020.

Knight F. (1921) *Risk, uncertainty and profit*. Houghton Mifflin Company, Boston/New York

Lekvall, P., and Wahlbin, C. (1973). A study of some assumptions underlying innovation diffusion functions. *Swedish Journal of Economics*, 75, 362-377.

Lotka, A.J. (1925). *Elements of Physical Biology*. Williams and Wilkens.

Mahajan, V., Muller, E., and Bass, F.M. (1990). New product diffusion models in marketing: a review and directions for research. *Journal of Marketing*, 54 (1), 1-26.

Massiani, J., and Gohs, A. (2015). The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. *Research in Transportation Economics*, 50, 17-28.

Meade, N., and Islam, T. (1998). Technological Forecasting: Model Selection, Model Stability, and Combining Models. *Management Science*, 44 (8), 1115-1130.

Meade, N., & Islam, T. (2001). *Forecasting the diffusion of innovations.* In J. S. Armstrong (Ed.), Principles of forecasting. Boston: Kluwer Academic Publishers.

Meade, N., and Islam, T. (2006). Modelling and forecasting the diffusion of innovation – A 25-year review. *International Journal of Forecasting*, 22, 519-545

Modis, T., and Debecker, A. (1992). Chaoslike states can be expected before and after logistic growth. *Technological Forecasting and Social Change*, 33, 267-278.

Park, S. Y., Kim, J. W., and Lee, D. H. (2011). Development of a market penetration forecasting model for hydrogen fuel cell vehicles considering infrastructure and cost reduction effects. *Energy Policy*, 39(6), 2207-3315.

Parker, P. (1994). Aggregate diffusion forecasting models in marketing: A critical review. *International Journal of Forecasting*, 10, 353-380.

Pearl, R., and Reed, LJ (1920). On the Rate of Growth of the Population of the United States since 1790 and Its Mathematical Representation. *PNAS*, 6, 6, 275-288.

Peres, R., Muller, E., and Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing*, 27, 91-106.

Robinson, J. (1982). Energy Backcasting: A proposed method of policy analysis. *Energy Policy*, 10, 337-344.

Robinson, J. (1990). Futures under glass: a recipe for people who hate to predict, *Futures*, 22, 8, 820-842.

Rogers, E. M. (1962). *Diffusion of innovations.* New York: The Free Press,

Schmittlein, D.C., and Mahajan, V. (1982). Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance. *Marketing Science*, 1, 57-78.

Schmoch, U. (2007). Double-boom cycles and the comeback of science-push and market-pull, *Research Policy 36*, 1000-1015.

Srinivasan, V., and Mason, C.H. (1986). Technical Note-Nonlinear Least Squares Estimation of New Product Diffusion Models. *Marketing Science*, 5 (2), 169-178.

Steffens, P. R. (2003). A model of multiple unit ownership as a diffusion process. *Technological Forecasting and Social Change*, 70, 901-917.

Sternman, J.D. (2011). Communicating climate change risks in a skeptical world. *Climatic Change*, 108, 811-826.

Stoneman, P. (2002). *The economics of technological diffusion.* Cambridge, MA: Blackwell.

Takada, H., and Jain, D. (1991). Cross-national analysis of diffusion of consumer durable goods in Pacific rim countries. *Journal of Marketing*, 55, 48-54.

The Economist (2017). The death of the internal combustion engine. *The Economist*, Aug 12th 2017 edition.

Urban, G. L., Weinbert, B. D., and Hauser, J. R. (1996). Premarket forecasting of really-new products. *Journal of Marketing*, 60, 47-60.

Van den Bulte, C., and Lilien, G. L. (1997). Bias and systematic change in the parameter estimates of macro-level diffusion models. *Marketing Science*, 16, 338-353.

Venkatesan, R., and Kumar, V. (2002). A genetic algorithms approach to forecasting of wireless subscribers. *International Journal of Forecasting*, 18(4), 625-646.

Venkatesan, R., Krishnan, T., and Kumar, V. (2004). Evolutionary estimation of macro-level diffusion models using genetic algorithms: An alternative to nonlinear least squares. *Marketing Science*, 3, 451-464.

Verhulst, P.F. (1838). Notice sur la loi que la population suit dans son accroissement. *Correspondance mathématique et physique*, 10, 113–121.
Verhulst, P.F. (1845*) "Recherches mathématiques sur la loi d'accroissement de la population" [Mathematical Researches into the Law of Population Growth Increase]*. Nouveaux Mémoires de l'Académie Royale des Sciences et Belles-Lettres de Bruxelles.

**TABLE 1**

**Key figures on European and US fleets**

| | **Europe** | **United States** |
|---|---:|---:|
| Number of cars (2016, mio) | 259.7 | 113 (out of 269) |
| New annual registrations (2016, mio) | 15 | 6.3 |
| Average age | 11 | 11.6 |
| Renewal period (in years) | 17 | 18 |
| Market share (2017) of BEVs | 0.12% | 0.35% |

**TABLE 2**

**Cumulative sales data on Battery EVs in Europe and United States, from 2011 to 2017**

(Sources: European Environment Agency; US Department of Energy – Energy Efficiency and Renewable Energy, hybridcars.com)

| **Year** | **Stock BEVs in Europe** | **Stock BEVs in US** |
|---|---:|---:|
| 2011 | 8,493 | 10,060 |
| 2012 | 22,479 | 24,710 |
| 2013 | 46,654 | 72,404 |
| 2014 | 84,509 | 135,820 |
| 2015 | 141,265 | 206,864 |
| 2016 | 205,581 | 293,595 |
| 2017 | 302,724 | 398,066 |

**TABLE 3**

**Overview of the heuristics deployed, illustrated with the BEV case.**

| **Steps** | **BEV application** |
|---|---|
| 1. Select an appropriate diffusion model | Bass model |
| 2. Define the relevant parameter variations | Parameter m (10), p (250) and q (200) |
| 3. Elaborate the search grid, based on all possible parameter combinations | Calculate 500,000 times series reflecting all parameter combinations per region |
| 4. Introduce the goodness-of-fit calculus (loss function) | Calculate the loss function for each combination (500,000) |
| 5. Set a threshold to identify 'more likely' scenarios | $R^2 > 0.99$ |
| 6. Assess and interpret these 'more likely' scenarios in terms of impact and timing | 689 for EU and 1,864 for US |

**TABLE 4**

**Market share distribution of the more likely scenarios (i.e. $R^2$ >.99)**

| **Market share** | **Europe**[10] | | **United States** | |
|---|---|---|---|---|
| | *Count* | *%* | *Count* | *%* |
| 10% | 234 | 33.96% | 646 | 34.66% |
| 20% | 117 | 16.98% | 320 | 17.17% |
| 30% | 79 | 11.47% | 211 | 11.32% |
| 40% | 58 | 8.42% | 157 | 8.42% |
| 50% | 47 | 6.82% | 128 | 6.87% |
| 60% | 40 | 5.81% | 104 | 5.58% |
| 70% | 34 | 4.93% | 91 | 4.88% |
| 80% | 29 | 4.21% | 78 | 4.18% |
| 90% | 27 | 3.92% | 67 | 3.59% |
| 100% | 24 | 3.48% | 62 | 3.33% |
| Total | 689 | 100.00% | 1,864 | 100.00% |
| | | | | |
| Parameter | Min | Max | Min | Max |
| p value | 0.00003 | 0.00067 | 0.00012 | 0.00241 |
| q value | 0.28 | 0.62 | 0.23 | 0.51 |

[10] Including the observation of the *first* available year in Europe (i.e., a stock of 734 BEVs in 2010) would lower the valid p-interval to [0.00002 – 0.00039] and narrow the valid q-interval down to [0.35 – 0.65]. However, including this observation does not impact the overall market share distribution of these *more likely* scenarios, nor the distribution in the market share intervals of [1 – 10%] and [11 – 20%]. One could then question the relevance of point estimating the optimal values of the model parameters, when excluding (or 'missing') just one observation (i) yields more optima (with a similar distribution pattern); and (ii) broadens the scope of the valid parameter intervals.

## TABLE 5A

### Descriptive statistics: Battery Electric Vehicles in Europe ($R^2$ >.99; n = 689)

| | Market Share | | | New BEV entrants | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Year* | *Min* | *Max* | *Average* | *Min* | *%* | *Max* | *%* | *Average* | *%* |
| 2018 | 0.14% | 0.21% | 0.17% | 94,842.45 | 0.63% | 209,073.06 | 1.39% | 142,279.99 | 0.95% |
| 2019 | 0.19% | 0.34% | 0.25% | 120,973.19 | 0.81% | 334,308.92 | 2.23% | 205,002.86 | 1.37% |
| 2020 | 0.25% | 0.54% | 0.36% | 153,625.62 | 1.02% | 536,374.07 | 3.58% | 295,724.01 | 1.97% |
| 2021 | 0.33% | 0.87% | 0.53% | 194,637.12 | 1.30% | 865,711.82 | 5.77% | 426,521.91 | 2.84% |
| 2022 | 0.42% | 1.41% | 0.76% | 245,866.94 | 1.64% | 1,394,049.40 | 9.29% | 613,824.53 | 4.09% |
| 2023 | 0.54% | 2.27% | 1.10% | 309,414.45 | 2.06% | 2,236,480.79 | 14.91% | 878,809.56 | 5.86% |
| 2024 | 0.69% | 3.64% | 1.58% | 387,536.35 | 2.58% | 3,566,484.40 | 23.78% | 1,246,345.07 | 8.31% |
| 2025 | 0.87% | 5.80% | 2.25% | 482,474.00 | 3.22% | 5,632,586.38 | 37.55% | 1,740,927.43 | 11.61% |
| 2030 | 2.60% | 44.74% | 10.06% | 963,331.00 | 6.42% | 33,226,959.65 | 221.51% | 5,795,495.99 | 38.64% |
| 2035 | 5.81% | 96.54% | 22.58% | 9,605.36 | 0.06% | 30,465,122.01 | 203.10% | 5,991,332.30 | 39.94% |
| 2040 | 8.62% | 99.96% | 30.44% | 75.99 | 0.00% | 22,995,334.31 | 153.30% | 2,850,446.76 | 19.00% |
| 2045 | 9.69% | 100.00% | 33.41% | 0.60 | 0.00% | 17,498,443.39 | 116.66% | 882,939.14 | 5.89% |

## TABLE 5B

**Descriptive statistics: Battery Electric Vehicles in the United States ($R^2 > .99$; n = 1.864)**

| | Market Share | | | New BEV entrants | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Year* | *Min* | *Max* | *Average* | *Min* | *%* | *Max* | *%* | *Average* | *%* |
| 2018 | 0.42% | 0.59% | 0.50% | 110,782.01 | 1.76% | 229,429.25 | 3.64% | 160,395.34 | 2.55% |
| 2019 | 0.54% | 0.89% | 0.69% | 135,115.97 | 2.14% | 342,238.81 | 5.43% | 216,096.31 | 3.43% |
| 2020 | 0.69% | 1.34% | 0.95% | 164,089.37 | 2.60% | 509,073.63 | 8.08% | 290,308.03 | 4.61% |
| 2021 | 0.87% | 2.01% | 1.29% | 198,232.88 | 3.15% | 754,041.18 | 11.97% | 388,068.01 | 6.16% |
| 2022 | 1.08% | 2.99% | 1.75% | 237,955.46 | 3.78% | 1,109,863.86 | 17.62% | 514,728.15 | 8.17% |
| 2023 | 1.33% | 4.42% | 2.34% | 283,433.33 | 4.50% | 1,624,951.99 | 25.79% | 675,048.50 | 10.72% |
| 2024 | 1.62% | 6.50% | 3.12% | 334,464.23 | 5.31% | 2,370,263.32 | 37.62% | 871,717.74 | 13.84% |
| 2025 | 1.97% | 9.50% | 4.09% | 390,293.67 | 6.20% | 3,411,936.13 | 54.16% | 1,103.547.44 | 17.52% |
| 2030 | 4.45% | 47.68% | 12.47% | 279,620.46 | 4.44% | 12,721,709.69 | 201.93% | 2,378,727.59 | 37.76% |
| 2035 | 7.36% | 93.57% | 23.26% | 9,097.15 | 0.14% | 10,794,821.77 | 171.35% | 2,203,456.31 | 34.98% |
| 2040 | 9.13% | 99.75% | 29.97% | 255.08 | 0.00% | 8,075,804.28 | 128.19% | 1,073,685.46 | 17.04% |
| 2045 | 9.76% | 99.99% | 32.67% | 7.12 | 0.00% | 6,315,365.90 | 100.24% | 373,617.39 | 5.93% |

**FIGURE 1A**

**Comparison of the observations (i.e., red dotted line) with the *more likely* scenarios ($R^2$ >.9965) in Europe**

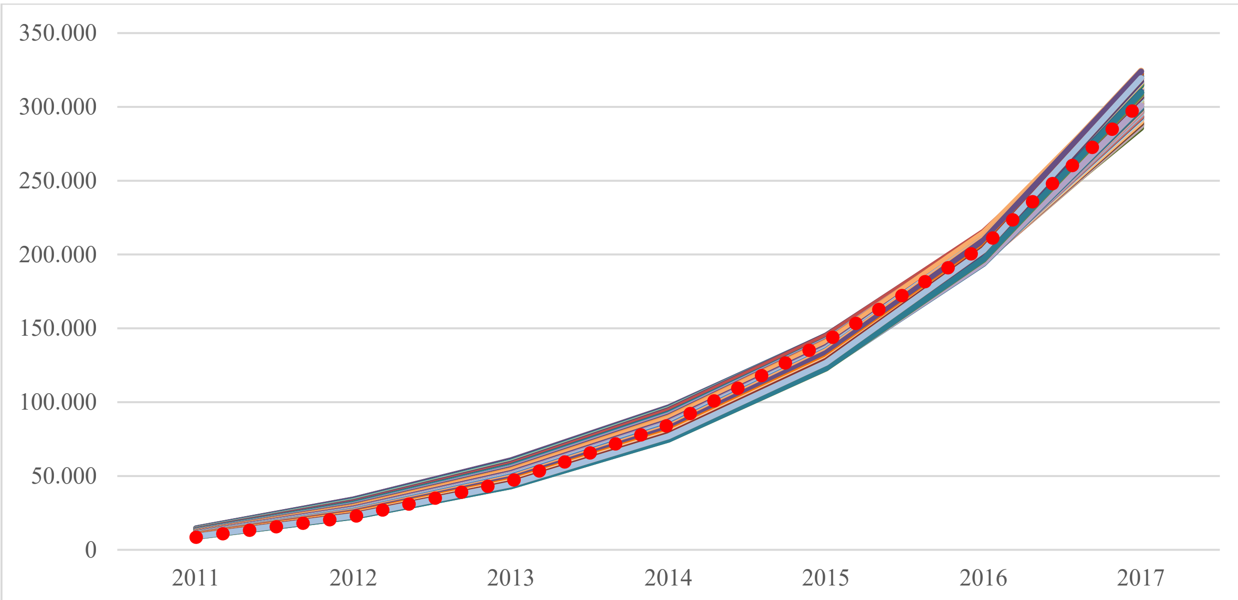



**FIGURE 1B**

**Comparison of the observations (i.e. red dotted line) with the *more likely* scenarios ($R^2$ >.9965) in the US**

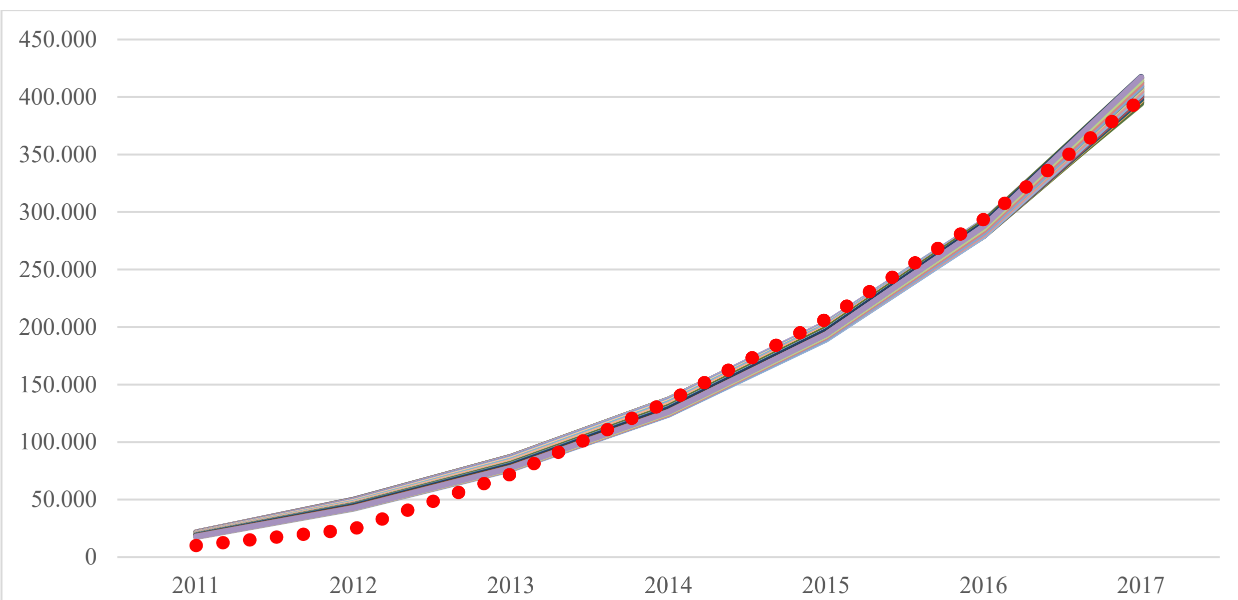


**FIGURE 2A:**

**More likely scenarios ($R^2$ >.9965) for Battery EVs in Europe (n = 211)**

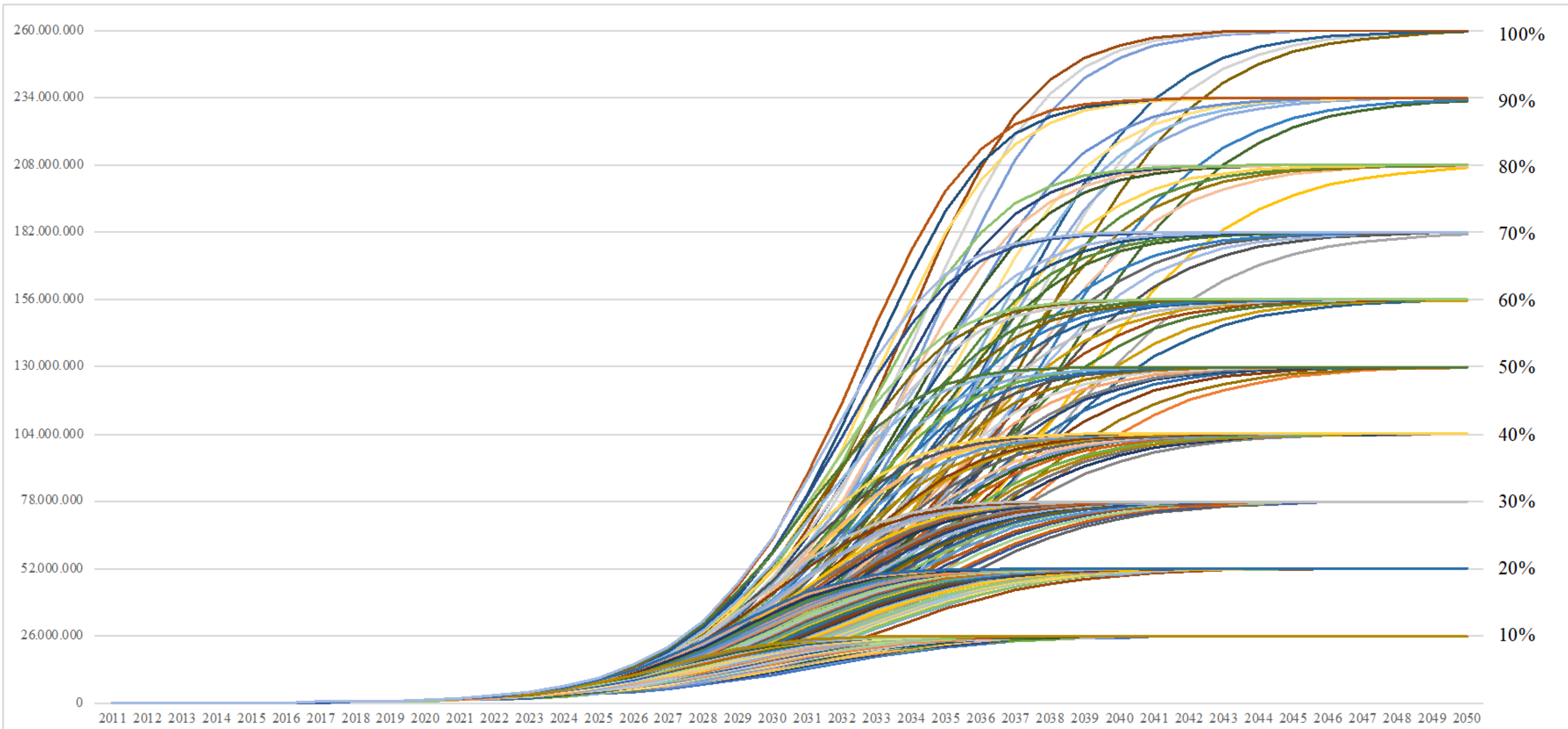
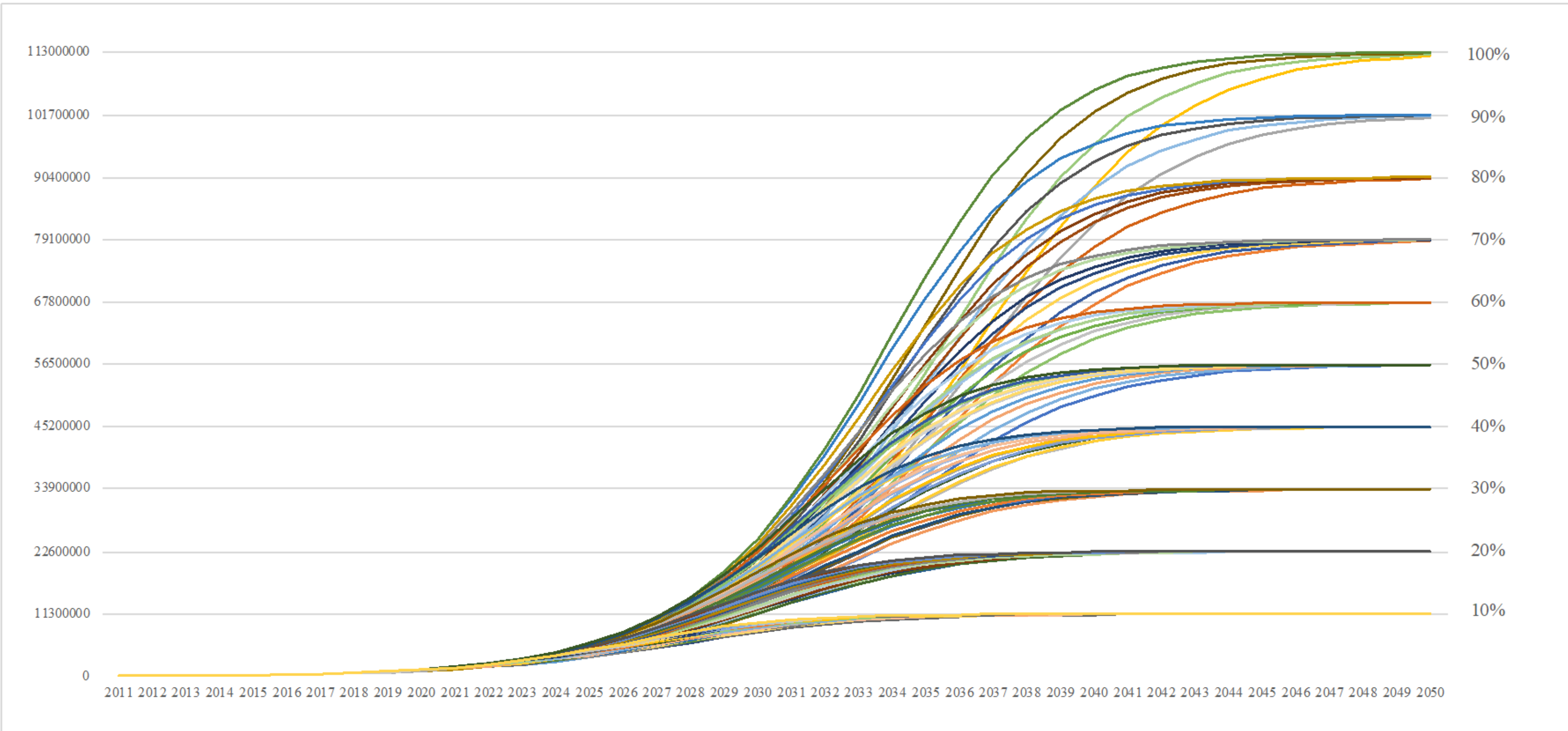


**FIGURE 2B:**

**More likely scenarios ($R^2$ >.9965) for Battery EVs in the US (n = 148)**



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