A Simulation-Based Innovation Forecasting Approach Combining the Bass Diffusion Model, the Discrete Choice Model and System Dynamics

An Application in the German Market for Electric Cars

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Abstract—**This work presents a novel simulation-based forecasting approach combining concepts from the Bass Diffusion Model and the Discrete Choice Model from a System Dynamics perspective. The proposed approach allows for the forecasting of the adoption rate and its timing, by understanding the underlying preferences of individual customers and social forces influencing it. A real-scale preliminary application in the German market for electric cars, parameterized through a Conjoint Analysis, is provided. Simulation results indicate that battery charging technology and infrastructures are crucial for the success of electric cars in Germany.**

Keywords—Forecasting Innovation; System Dynamics; Bass Diffusion Model; Discrete Choice Model; Conjoint Analysis; Electric Vehicles (EV); German Electric Car Market.

I.   INTRODUCTION

Understanding the adoption process of new products is crucial for most businesses. It is also important for governments when creating policies to regulate the market or to define the necessary infrastructure to support new technologies being introduced, such as medical equipment or electric vehicles.

Although largely investigated since the last century, diffusion processes still remain complex phenomena. Various methodologies, approaches and computer models have been developed to investigate the market diffusion of new products.

In order to contribute to the scientific advancement in this area, this paper proposes a novel simulation-based approach for evaluating how consumers' preferences and social forces influence the introduction of new products. The proposed approach merges concepts from the traditional Bass Diffusion Model with the Discrete Choice Model from a System Dynamics perspective. Compared to other approaches, our model offers the following advantages: a. both timing and market-share can be jointly estimated; b. the model is fully flexible with respect to the number of product attributes, and; c. the model is easily parameterized through Conjoint Analysis without the need of market data. This is illustrated by the real-scale application to the German market for electric cars. The results demonstrate the potential of the proposed approach, to support the understanding of the main drivers for product adoption.

This paper is organized as follows: section II presents a literature review and highlights the research gap; section III overviews the theoretical background employed in the proposed model; section IV introduces the proposed approach; section V presents the preliminary application in the German market for electric cars; section VI proposes future research; and finally, section VII outlines final remarks and conclusions.

II.   RELATED WORKS

A myriad of innovation forecasting studies is provided in the literature. The present work concerns Diffusion models, Discrete Choice Models and System Dynamics approaches, as well as the ones applied in the electric car market.

The Bass Diffusion Model [1] is probably the most widely used approach in management science [2]. In its algebraic form, the Bass Model is somewhat restricted to a small set of parameters and strong underlying assumptions. Some works partially relaxed some of these assumptions (e.g. Dodson and Muller [3]) and others extended the model (e.g. Kalish [4], Chatterjee and Eliashberg [5], and Horsky [6]). Interestingly, Bass [2] himself commented on some possible extensions for his seminal work. Two relatively recent state-of-the-art reviews are provided in Frenzel and Grupp [7] and in Meade and Islam [8].

While the Bass Diffusion Model captures innovation timing, the Discrete Choice Model, another popular approach, captures consumers' appraisal of the product's utility [9]. Many interesting works exist in the literature, including Anas [10], that relates information theory with Discrete Choice Models; Drakopoulos [11] discusses the psychological aspects underlying the theory of rational consumers; Kim et al. [9] propose an adjusted Discrete Choice Model that incorporates the choice behavior of the consumer into the dynamics of product diffusion; Lee et al. [12] put forward a methodological framework derived from a static utility function based on the Discrete Choice Model and the Bass Diffusion Model.

System Dynamics is also employed in this area. Milling [13] provides an example of the innovation diffusion process from a System Dynamics perspective. The basic structure of his model is identical to the mixed-influence of the Bass model [14], thus the characteristics of the product are not considered explicitly. Mooy [15] used a System Dynamics model with the sociological theory of Memetics, and more recently Park et al. [16] developed a marketing penetration forecasting model for hydrogen vehicles, also using a generalized Bass model in a System Dynamics framework.

Maier [14] explains that variables such as pricing, quality, technical capabilities, etc. can impact on the probability of a purchase, but in his case this probability serves as a multiplier that affects the coefficient of innovation and imitation, or that can delay or speed up the demand. The total product utility is not considered explicitly through a Discrete Choice perspective.

More specifically in the electric car market, many works propose forecasting approaches in the literature, including Discrete Choice (e.g., Beggs [17]), conjoint experiments (e.g., Segal [18], Ewing and Sarigolli [19]), and equation-based models (Urban et al. [20]). An approach quite related to the present work is Klasen and Neumann [21], which combines the Bass Diffusion Theory with the Discrete Choice Model in an agent-based framework to investigate the feasibility of the German's goal for the electric car's adoption rate in next decade. Another contribution from the literature, which is close to the present work, is Meyer and Winebrake [22], but it is dedicated to hydrogen vehicles and the refueling infrastructure. Similarly to the present work, their System Dynamics model encapsulates concepts from the Diffusion Theory and the Discrete Choice Model, but consumers' preference utilities are limited to fuel cost, vehicle price and station density. Moreover, the proposed model does not directly incorporate social forces in a utility model.

Despite their contribution to the concerned literature, and to the best of the authors' knowledge, no work exists which deals directly with consumer preferences and diffusion processes within a System Dynamics perspective for the electric car market. Thus, the model and application domain proposed herein are original.

III. THEORETHICAL BACKGROUND

This section introduces the main concepts employed in the proposed model.

A. Bass Diffusion Model

Traditionally, economic models of innovations' diffusion are founded on biological and sociological research [23]. Perhaps the most well known work in the area is the Bass Diffusion Model [1], which distinguishes between two types of customers: innovators and imitators. This model is described as a set of differential equations employing a small number of parameters. Basically, Bass defined the rate of adoption $S(t)$ as a function of the potential market share $T(t)$, the actual number of adopters $A(t)$, an innovation coefficient p and an imitation coefficient q. Bass formulated it is as following:

$$S(t) = qT(t) + (p - q)A(t) - p[A(t)]^2/T(t). \qquad (1)$$

The Bass model assumes that everything in a diffusion process (e.g., customers' individual characteristics, availability of information about a product, positive and negative personal recommendations, etc.) can be modeled through the parameters q and p. Despite the fact that the Bass model is largely used, its inherent assumptions have been criticized in the literature [8]. Additionally, the Bass Model is not easily parameterized when no market data is available. Thus, radically new products, which imply changes in consumers' behavior, as the electric car, does restrict the use of the Bass Diffusion Model.

Diverse approaches have emerged to improve or extend the Bass model, including the Discrete Choice Model and System Dynamics [21].

B. Discrete Choice Model

The Discrete Choice Model allows for the determination of the relative purchase probability based on products' utilities [24], describing products as a finite set of perfectly substitutable attributes. In short, the probability P_i^k that an individual i will choose a product k from a set of alternatives A_i is given by:

$$P_i^k = 1/\left(1 + \sum_{l \in A_i, l \neq k} e^{(V_i^k - V_i^l)}\right), \qquad (2)$$

where V_i^k is the deterministic component of the utility, described through expressed attitudes toward that alternative. This utility is assumed to be a linear additive function of the product attribute score, such as:

$$V_i^k = \sum_{j \in S^k} a_j^k x_{ij}^k + \sum_{j \in S} b_j x_{ij}^k, \qquad (3)$$

Where x_{ij}^k is the score given by individual i to the kth product alternative of the jth attribute; a_j^k is the utility weight reflecting the importance of the jth attribute defined uniquely for the kth alternative; b_j is the utility weight reflecting the importance of the jth generic attribute defined consistently for all alternatives; S^k is the set of attributes relevant to alternative k only, which is not common to all other alternatives and; S is the set of attributes common to the description of all available alternatives.

It is important to note that both (2) and (3) assume that the individual preferences structure is fixed and depends only on the product attributes, which contradicts one fundamental notion of the Bass diffusion Model, i.e., that preference is also influenced by social forces (e.g. interaction between adopters and non-adopters) through time [21]. Thus, innovation timing cannot be forecasted directly through the use of Discrete Choice Models. This opens interesting opportunities by combining both diffusion and the Discrete Choice Model to incorporate social aspects and consumer preferences. Moreover, the linear structure of equation (3) enables the identification of its coefficients through a least square analysis, using a Conjoint Experiment, even in the case where products are fictitious. Thus, the combination of the Bass with the Discrete Choice Model allows one to

forecast not only purchase probability based on product attributes, but also diffusion timing, with a relatively simple form of parameterization, namely, conjoint experiment. System Dynamics provides an interesting framework for doing so.

C. System Dynamics Applied to Innovation Diffusion

System Dynamics is an approach for modeling and understanding the behavior of complex systems over time through the study of the system's information-feedback structure. Thereby, interactions among the system structure, amplification in policies and time delays in decision and actions can be analyzed [25]. Basically, the mathematical description of a system dynamic model is realized with the help of differential equations. These equations simulate the resulting behavior of the system over time. The basic elements of the system dynamics model are feedbacks, flows, accumulation of flows (i.e. stocks) and time delays.

The coarse structure of the Bass model is roughly schematized as a System Dynamics model in Fig. 1 (for a detailed explanation of System Dynamics and the Bass model, please refer to Sterman [26]).
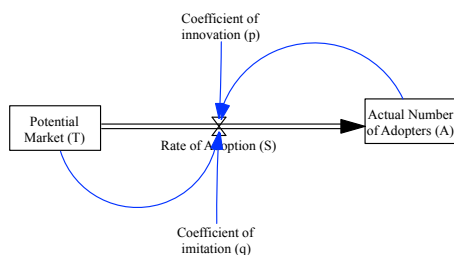

Figure 1: Bass model from a system dynamics' perspective (inspired by [14]).

In this case, the rate $S(t)$ consumes the stock $T(t)$ and feeds stock $A(t)$, regulated by parameters p and q. In contrast with Bass' original algebraic formulation, the System Dynamics model easily allows diverse policy studies, such as a change in parameters p and q, or even structural changes, such as adding other feedback loops, for example. Consequently, System Dynamics provides an interesting framework to combine the fundamental structure of the Bass Model (to take into consideration innovation timing and social aspects of the diffusion process) with the basic ideas of Discrete Choice Models (incorporating customers' preferences explicitly in accordance with several products' attributes). In the next section, a model describing this possibility is discussed.

IV. PROPOSED METHODOLOGY AND SIMULATION MODEL

The general methodology employed in this work is summarized in Fig. 2 and explained afterwards.
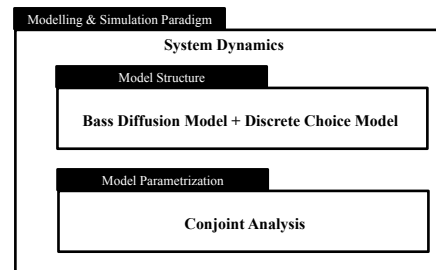

Figure 2: Proposed methodology.

A. Modelling and Simulation Paradigm

The proposed System Dynamic model is depicted in Fig. 3.

This figure shows that the basic structure of the Bass Model (see Section IIIA) is employed, including the typical $A(t)$, $S(t)$ and $T(t)$. In addition, the traditional Bass model is extended in many ways. First, based on Sterman [26], the model captures the replacements/substitutions purchases by the variable discarding rate DR^k of the product alternative k. This is necessary because for the electric car (and many other durables), the adoption timing is slow and can easily overcome the product's life cycle. In this case, based on the car's lifecycle lc, obsolete products have to be replaced, moving consumers back to the potential market when the product is discarded. The rate at which consumers move back was modeled approximately as the adoption rate $S(t)$, delayed by the average lifecycle lc of the product. As the average lifecycle is relatively long for many durables (like cars), the repeated purchase decisions are reasonably similar to the initial purchase decisions; thus after discarding consumers reenter the potential customers' pool [26].
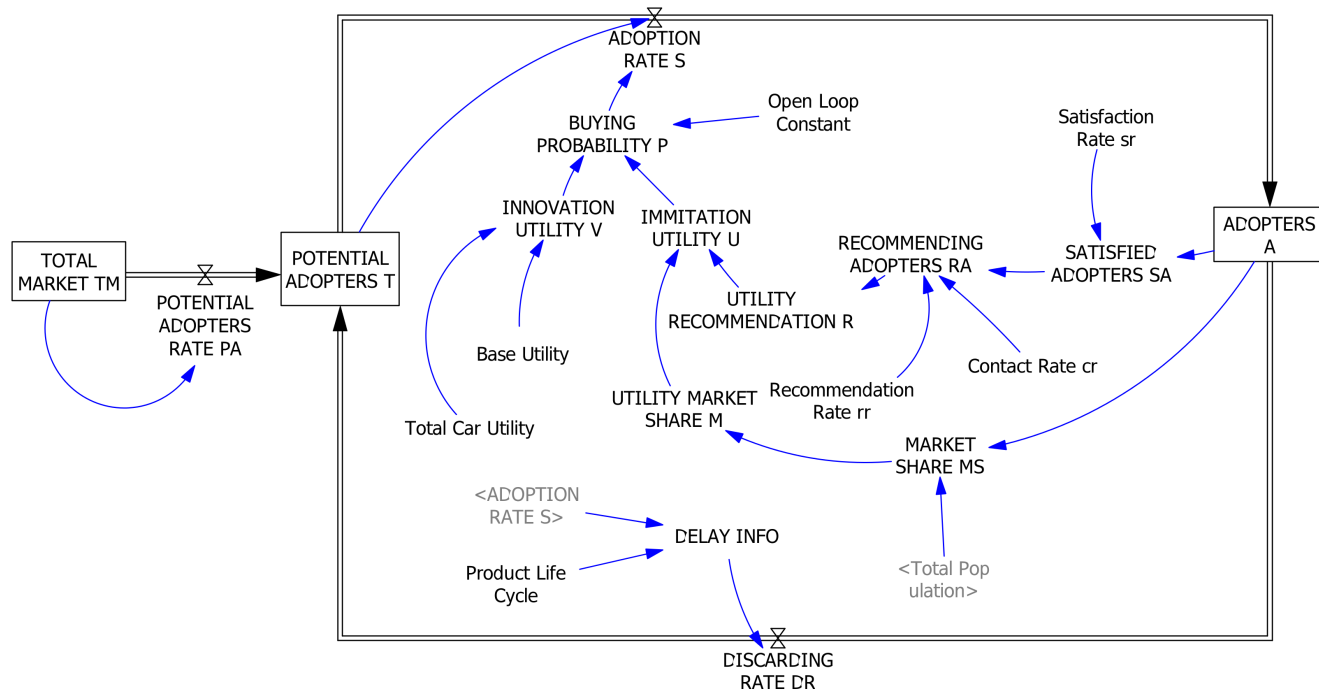
Figure 3: Proposed model.

Another improvement to the traditional model is the inclusion of the total market *TM*(*t*), which represents the untapped market, as suggested by Maier [14]. The stock of potential adopters is increased by *PA*(*t*) rate, i.e. the flow coming from the untapped market, which represents actual consumers of other products that may become new customers at a rate that also depends on the average product lifecycle *lc*. This corrects the traditional diffusion model for the substitution of durables, because not all consumers are immediately available as potential adopters, but only those that need to replace the product after it reaches the end of its lifecycle. Based on this, it is possible to define:

$$A(t) = \int_{t_0}^{t} (S(t) - DR(t)) dt, \qquad (4)$$

$$S(t) = P \times T(t), \qquad (5)$$

where *P* is explained in the next subsection and,

$$DR(t) = S(t - lc), \qquad (6)$$

i.e., the discarding rate is delayed by the lifecycle *lc* in respect to *t*, and:

$$T(t) = \int_{t_0}^{t} (PA(t) + DR(t) - S(t)) dt, \qquad (7)$$

$$PA(t) = (Total\ Population)/lc, \qquad (8)$$

$$TM(t) = Total\ Population - \int_{t_0}^{t} PA(t) dt. \qquad (9)$$

The most important contribution of the proposed model is indicated at the center of Fig. 3. Replacing the traditional coefficients *p* and *q*, the buying probability is determined through a model inspired by the Discrete Choice approach combined with the Diffusion Theory, as explained in the next subsection. In this way, the ideas underlying the Bass Model are maintained with the advantage of easy parameterization through Conjoint Analysis, even in the case of radical innovations when no market data is available.

B. Model Structure for the Buying Process

The fundamental structural contribution of the proposed model lies on the substitution of buying probabilities by the innovation and imitation coefficients. It was assumed that both innovative and imitative behaviors originate though utility assessment, as proposed by Klasen and Neumann [21]. A similar approach was also recently employed by Goldenberg et al. [27]. In this case, P_i^k is not calculated through (2) as the traditional Discrete Choice Model, since the utility assessment of products V_i^k is replaced by VS_i^k:

$$VS_i^k(t) = V_i^k(t) + U_i^k(t), \qquad (10)$$

where $V_i^k(t)$ is defined in (3) and represents the innovation utility, similarly to the innovation coefficient *p* of the Bass model; $U_i^k(t)$ is the imitation utility of a product alternative *k* for individual *i*, representing the coefficient *q* of Bass. By doing so, besides incorporating consumer preferences as preconized by the Discrete Choice Model, equation (10) combines characteristics of the classical diffusion model, including social components. These social components are derived from the perception of clients of the market share

and positive recommendations from their entourage, as following:

$$U_i^k(t) = R_i^k(t) + M_i^k(t), \qquad (11)$$

where $R_i^k(t)$ represents the utility of positive recommendations and $M_i^k(t)$ the utility of the market share:

$$R_i^k(t) = f(RA_i^k(t)), \qquad (12)$$

$$M_i^k(t) = g(MS^k(t)), \qquad (13)$$

where $RA_i^k(t)$ represents the quantity of recommending adopters for the kth alternative obtained by individual i; and $MS^k(t)$ is the market share (percentage) of the kth alternative. Both functions f and g are parameterized with the help of a conjoint experiment, explained in the next subsection. $RA_i^k(t)$ and $MS^k(t)$ are calculated as follows:

$$RA_i^k(t) = rr_i^k \times cr_i^k \times SA^k(t), \qquad (14)$$

$$MS^k(t) = A(t) \times sr^k, \qquad (15)$$

where rr_i^k is the recommendation rate for the kth alternative received by individual i; cr_i^k is the contact rate of individual i with people who adopted the kth alternative; $SA^k(t)$ is the quantity of satisfied adopters choosing the kth alternative; sr_i^k is the satisfaction rate of those adopting the kth alternative; and the already defined $A(t)$ is the total quantity of adopters.

C. Model Parametrization

In order to parameterize the simulation model, the proposed methodology employs a conjoint experiment. The Conjoint Analysis is probably the marketers' favorite methodology for determining how consumers decide among competing products, according to Green et al. [28]. Basically, it measures trade-offs of survey responses concerning preferences and intentions to buy. A conjoint experiment is performed through a field research employing interviews and semi-structured questionnaires with potential consumers. The results are the consumers' individual utility functions for each product attribute (in equation 3).

In the present work, these utility functions constitute the necessary parameters for the utility loop in Fug. 3. As mentioned before, both functions f and g are produced based on a Conjoint Analysis. For f, based on quantities of recommending adopters $A(t)$, it was possible to define the values of the corresponding utility function of positive recommendations $R_i^k(t)$. Similarly, based on the possible market share $MS^k(t)$, it was possible to determine the corresponding utility function of the market share $M_i^k(t)$. Finally, the innovation utility V_i^k was determined from the sum of the *total car utility* and the *base utility*, both resulting from the Conjoint Analysis. The *total car utility* corresponds to the consumer's average utility of an assumed technology. The *base utility* can be interpreted as a utility deficit of some product alternatives in relation to others. This deficit can be explained by different reasons, e.g. product or technology related uncertainty, lack of information and residual preferences not measured by other products' attributes. For further detail on Conjoint Analysis, the reader is referred to Ewing and Sarigollii [19], Klasen and Neumann [21] and Lee et al. [12].

V. PRELIMINARY APPLICATION

The proposed simulation model was applied in a preliminary industrial-scale case in the German market for electric cars.

A. Simulation Problem

As a promising technology to reduce greenhouse gas emissions, the electric car appears, together with other complimentary technologies such as hybrid cars, to be an interesting alternative for consumers. Believing that it is a good alternative, the German government has established an official market goal of 1.000.000 cars sold by 2020, a market share of approximately 2,32%. Recent governmental reports suggest, though, that without government intervention, only 450.000 cars will be sold [9]. Great uncertainty is related to this market, since consumers' reaction to technological limitations, loading infrastructure and green energy generation are still not well understood.

Consequently, understanding the market potential and consumers' preferences is crucial not only for validating the market goal but also for deriving public policies to support new technological and infrastructural developments. As explained in section II, many works propose approaches to forecast the electric car market in the literature, but to the best of the authors' knowledge, no work puts forward an approach dealing directly with consumer preferences and diffusion processes within a system dynamics framework, such as the one proposed herein.

This approach provides an interesting simulation tool to forecast the market share when consumers' preferences favor technical attributes, such as in the electric car market. In addition, it allows for evaluating how social aspects and the product's utility influence the adoption process.

Thus, in this context, the preliminary simulation experiment aims at "*understanding how the main driver of infrastructure, the battery loading time, influences the diffusion of electric cars in Germany*". This simulation objective highlights that the main goal of the simulation study lies in the comparative analysis of different charging technologies. Consequently, absolute forecasting accuracy was not primarily pursued. Also, the scope of the study was limited to the comparison between present internal combustion cars and electric vehicles.

Based on the literature and on the interaction with some automakers, a list of 18 attributes that differentiate an electric car from a conventional one was produced and verified through interviews with two experts, one from the automobile industry and another from a consulting firm. Among the attributes, but not limited to them, price, battery range, variable cost per km, battery charging time, battery durability, CO_2 emissions, maximal velocity, acceleration, loading space, noise level and model exclusivity were included. The simulated technology was based on the newly

announced Renault ZE technology, which offers a total range of 180 km and three battery loading possibilities: a normal 7 hours charging at home and/or at the working place, a 30 minutes fast charging and a five minutes battery exchange. As fast charging and battery exchange infrastructures require expensive investments, this simulation enables one to understand how the market can evolve in the case these infrastructures are indeed installed.

The field research consisted of 291 interviews with subjects, conducted between September and October 2009. From these, only those with relevant driving behavior, i.e. mainly city and short distance travellers, were identified as potential consumers. This filtering criterion yielded 183 potential consumers that effectively took part in the conjoint experiment. Thus, based on this proportion, the potential market for electric cars accounts for 63% of the total German car market. With the results of the conjoint experiment, the model was parameterized and simulations were performed, together with some sensitivity analysis.

B. Simulation and Results

The proposed model was implemented through Vensim® PLE 5.10d and then configured using information from the Conjoint Analysis, described previously.

Fig. 4 shows the simulation results of the potential market share (in percentage) for the three technologies: a normal 7 hours charging, a fast 30 minutes charging and a five minutes battery replacement.
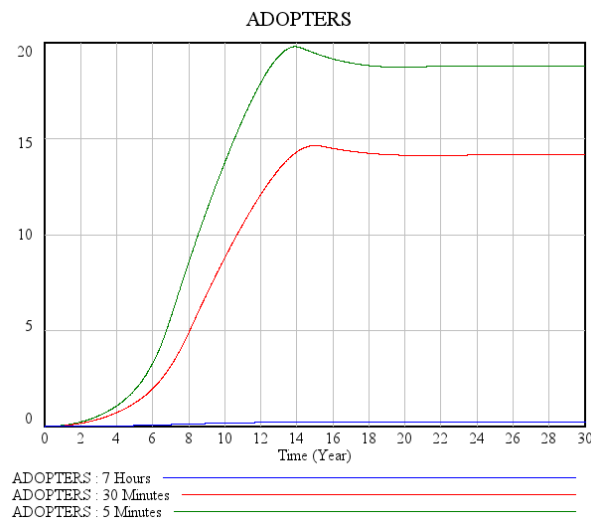

Figure 4: Simulation results for the potential market share.

A number of conclusions can be drawn from Fig. 4. First, if no fast charging infrastructure is available, consumers are not willing to purchase the electric car. The restrictions imposed by limited charging possibilities (only at work, at special public parking lots and at home), together with the long loading time, require a drastic change of consumers' behavior, leading to a less than 0,1% market share. Second, fast high-power charging infrastructure that allows the batteries to be charged in 30 minutes accounts for a market-share of 14% in 15 years. According to this scenario, the

German government goal of 1.000.000 cars (3,6% of the market) could be reached in 2020. The impediment lies on the infrastructure, which is not available yet. The latter requires not only high investment, but also time to be built, suggesting that the decision of the first cities where this infrastructure will be built is of a great strategic importance. Third, if battery exchange stations are available, the market-share might increase further, yielding 18% of the potential market (11% of the total market). Although this infrastructure requires a high investment in a stock of available batteries, it could account for a second step in the development of the market.

Even though our simulated experiment offers an idea of the potential market-share, results must be interpreted with care. Modeling assumptions and consumers' high uncertainty about the technology are possible sources of error. Despite the fact that absolute values should be read with caution, comparative analyses, as the one presented here, are valid. Thus, our analysis shows that investment in the right infrastructure can determine the success or failure of electric cars. In our analysis, we restricted ourselves to two main limitations of the electric car, i.e. the battery loading time and necessary infrastructure. Nevertheless, many other scenarios could be created and additional analysis could be done in future works, as discussed in the next section.

VI. FURTHER RESEARCH

The preliminary application illustrates the utility of the proposed model. Several additional studies can be performed using the proposed approach and dataset, including some supplementary validation.

An initial structural validation (which is the validity of the set of relations used in the model, as compared with the real processes) was performed based on the literature. This structural validation increases the level of certainty to acceptable levels. Some additional research efforts will be done in the future to deeply verify some assumptions strongly influencing the forecasting behaviour and accuracy. This additional validation effort will also be done through additional literature review in specific areas related to these assumptions.

Another important future work in the electric car market refers to the study of other drivers of the adoption process, such as car price when compared to conventional vehicles, battery durability, maximum speed, and so forth.

Other market sectors can be also investigated in the future, consequently more statistical certainty will be gained as other important application domains will be tested in the future.

Finally, additional works could be performed to develop simpler parameterization approaches in order to increase the model's usability in practice.

VII. CONCLUSIONS

This paper proposes a novel simulation-based approach for investigating the innovation adoption process. By combining the Bass Diffusion Theory with the Discrete Choice Model and Conjoint Analysis, from a System Dynamics perspective, it is possible to evaluate how

diffusion timing, social aspects and consumer preferences in terms of the products' characteristics influence the introduction of new products in the market.

An illustration of the proposed simulation model for the electric car market in Germany was provided. As a preliminary real-scale application, it was possible to demonstrate how battery charging technology and infrastructure drive customer adoption. This simulation experiment shows the potential of the proposed approach, supporting the understanding of the main drivers of product adoption in strategic planning through an intuitive method.

Several future research works are under way, including additional structural and behavioral validation efforts, as well as assumptions and parameterization investigations.

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