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Hydrogen-Fuel Infrastructure Investment with Endogenous Demand

A Real Options Approach

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Abstract

In this paper, we explicitly incorporate the impact that realized investment in new infrastructure has on adoption speed in a real options framework for investment decisions and analyze the consequences of this dependence for optimal investment. For the adoption diffusion process, we use a modified Generalized Bass Model. As an illustration, we apply the combined model to the case of the introduction of hydrogen- cars in the Netherlands. We perform a scenario analysis for six different infrastructure investment strategies combined with four different parameterizations. The results show that ignoring the potential interaction between the speed with which the required infrastructure will become available and the adoption process may lead to sub-optimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general.

Keywords: sustainable energy; investment uncertainty; compound real option; multi-stage investment; hydrogen infrastructure; generalized Bass model; scenario analysis;

JEL classification: D81, G32, Q42

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1. Introduction

Real option modeling has become an increasingly popular approach for the valuation of large infrastructural projects as well as the valuation of innovative projects in technology-intensive industries in recent decades. Examples that apply real option valuation to natural resources and energy problems include Sanders et al. (2013), Sarkar (2009), and Pless et al. (2016). Zhang et al. (2016) and Eckhause and Herold (2014) use real option methods to determine optimal funding and optimal subsidies in the field of sustainable energy.

The real option approach is preferable to net present value computations because it takes into account the value of waiting and operational flexibility: even with a negative NPV now, the project still may be profitable at a later point in time. Put differently, NPV may tend to undervalue a project. To operationalize the real option approach – or the NPV method for that matter – assumptions have to be made about the future demand for the new product or technology and the speed at which adoption will take place. In many applications, future demand is modelled exogenously and independently from the availability of the necessary infrastructure, see for instance Engelen, Kool and Li (2016) for the case of hydrogen investment.

In reality, the assumption of exogeneity of future demand may be unwarranted in some cases, especially when a costly infrastructure is required to successfully introduce a new technology. In such case, the speed and degree of adoption of the new technology may well depend on the availability of the infrastructure. [1] If so, an investment problem with chicken-egg characteristics may emerge: without sufficient infrastructure, consumers will not adopt the new technology; but without (likely) adoption, investors will not build the infrastructure. Put differently, supply and demand are interdependent. Obviously, appropriate modelling of the investment decision problem then needs to take this interdependency into account.

In this paper, we aim to contribute to the literature by explicitly incorporating the impact that realized investment in new infrastructure has on adoption speed in a real options framework and by analyzing the consequences of this dependence for optimal investment. This way, we jointly model the interdependency of demand and supply. To model the adoption process, we use a Generalized Bass Model – GB model – (see Bass, Jain, and Krishnan, 1994) which is

[1] Reid et al. (2016) recently argue that lack of re-charging infrastructure is one of the major hurdles facing the adoption of plug-in electric vehicles.

frequently used in business and marketing studies for the analysis of new products and technologies.

Subsequently, we illustrate the relevance of combining the GB model with the real options approach by applying it to the hydrogen case. It is generally acknowledged that the introduction of hydrogen-fueled cars would imply an expensive and time-consuming transition process involving a high degree of uncertainty, for instance with respect to technology, changes in government support and regulation, and future demand (Zhao and Melaina, 2006). Corresponding to the concept behind the GB model, we focus in particular on demand uncertainty and its dependence on the available supply of infrastructure. During the transition period, there is a significant challenge in matching the scale and timing of the fueling infrastructure investment with the actual hydrogen demand. Entry commitments involve sacrificing flexibility and increasing exposure to the uncertainties of new markets.

Theoretically, from the infrastructure provider's cost perspective it is important that there are just enough stations to ensure satisfactory utilization of each station and keep the cost as low as possible. An underutilized station drives up costs significantly. From a revenue perspective, the infrastructure investor aims at realizing a high adoption speed. For potential adopters, it is equally important that the number of refueling stations is more than sufficient. That is, consumers will perceive adequate refueling availability over a sufficiently large refueling coverage area as an important factor in their decision whether to switch hydrogen- cars.[2] This implies a choice between having higher fixed costs initially by building more stations at faster speed in combination with higher potential revenues due to higher and faster adoption on the one hand and investing at a slower speed with lower costs but also slower expected growth of revenues on the other hand. Deciding on a fast build-up of infrastructure will raise initial losses. Of course, it would be possible to pass through these costs into the price of hydrogen fuel, but that would make adoption less attractive in turn.

In particular, in our application we make the diffusion process – which models future demand – a function of the number of available refueling stations. Estimating this GB model for the hydrogen case directly is infeasible due to the lack of realized data. Instead, we do a scenario analysis where we combine six different investment strategies with four different parameterizations of the GB model. The variation in parameterization captures different degrees of demand sensitivity to existing infrastructure. The exploratory research will shed

[2] In addition to infrastructure investors and consumers, car producers are a third party involved that has to optimize its investment decision. For simplicity, we do not take this into account in the analysis.

light on the way the optimal investment path depends on the sensitivity of demand to available infrastructure and the consequent process of market penetration and provide direction for investors, policy-makers and decision-makers.

The paper is structured in the following way. The next section introduces the concept of innovation diffusion and concisely reviews the literature on modeling diffusion processes. In section 3, we briefly summarize the setup of the hydrogen investment case for the Netherlands. We develop the specific GB model which allows us to incorporate the sensitivity of demand to existing infrastructure in the optimal investment decision. Section 4 contains a scenario analysis based on the GB model to investigate the way the feasibility of investment depends on the sensitivity of demand on existing infrastructure. Section 5 concludes.

2. Innovation diffusion and market adoption

In this section, we introduce the concept of innovation diffusion and market adoption. In section 2.1, we first provide a broad graphical introduction using a stylized and simple diffusion process as presented by Rogers (2003) and discuss some of the complicating factors. In section 2.2, we briefly review the different strands in the literature with respect to the modeling of diffusion processes where we distinguish between the “aggregate” approach and the “individual choice” approach. Section 2.3 elaborates on the modeling strategies in the literature using the aggregate approach, as it fits the framework of our setup best.

For expositional reasons, the description and presentation of the diffusion process is kept simple and suggests innovation and adoption proceed at a predictable and linear pace. In reality, innovation processes can be highly non-linear and can be characterized by feedback loops and interactions between different phases. In this article we abstract from such complexities.

2.1. A stylized diffusion process

The origin of new technologies usually lies in principles and concepts found out by doing fundamental research. The adoption process typically begins by entering tiny niche markets. After that, the new technologies are validated in the demonstration phase: some of the technological uncertainties are resolved and much attention goes to integrating the technology in existing systems (e.g. integrating fuel cells in cars) and to reducing the complexity of the technology. When demonstrations are successful, the scale of demonstration projects may gradually increase. With the scale of projects, also the financial risks increase, especially because the future prospects of the technology may still be unclear. After the pre-commercialization phase, a technology moves into its early market phase. It starts to be of commercial interest for a specialized set of users, willing to take on a novel beneficial technology at slightly higher costs. The technology's market share may still increase and eventually the technology may become one of the incumbents, coexisting with, or even pushing out older technologies.

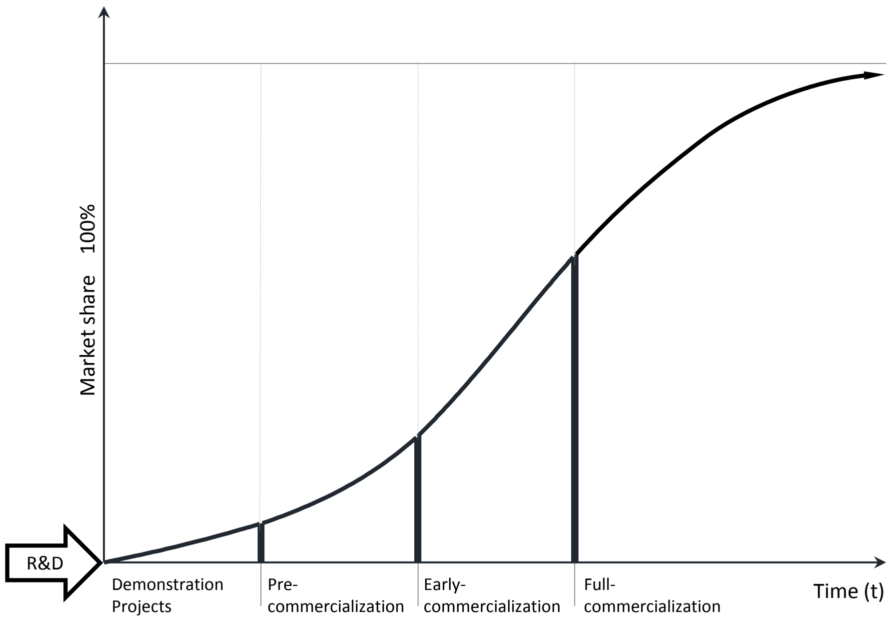

Figure 1. Cumulative adoption path

Figure 1 is adapted from Rogers (2003). The S-shaped curve plots the market share of an innovative technology against time or the amount of invested capital: slow initial improvement, then accelerated improvement, then diminishing improvement. These stages can be linked to the concepts of pre-commercialization, early commercialization and full commercialization indicated by the bold vertical bars. The S-curve can be used to gain insight into the relative payoffs of investment in competing technologies, as well as in providing some insight into when and why some technologies overtake others in the race for dominance.

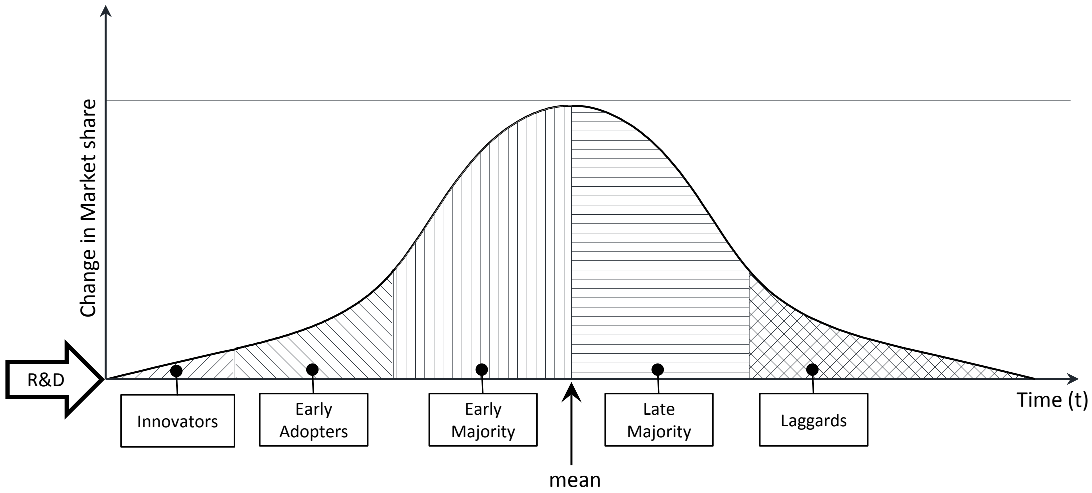

Figure 2. Characterization of adopter groups

While the S-shaped curve shows cumulative adoption as a percentage of market potential, the bell-shaped curve in figure 2 is a stylized way to reflect the adoption over specific periods. Rogers (2003) uses a figure like this to classify adopters of an innovation according to the timing of their adoption, under the assumption that the new technology eventually captures a 100% of the market. He defines the adopter categories on the basis of the normal distribution with the mean equal to the mean time to adoption (t_{mean}). The innovators (2.5%) are the ones that adopt earlier than the mean time minus two times the standard deviation (σ), the early adopters (13.5%) start using the new technology between t_{mean}-2σ and t_{mean}-σ, the early majority (34%) adopts between t_{mean}-σ and t_{mean}, the late majority (34%) between t_{mean} and t_{mean}+σ, and the laggards (16%) finally adopt after t_{mean}+σ.[3]

Overall, diffusion paths can and will be much more complex than the stylized curve in Figures 1 and 2. Mahajan, Muller and Srivastava (1990) criticize Rogers for the too rigid assumptions in his approach. They convincingly argue that in many cases the adoption process does not follow a normal distribution. In addition, there is no a priori reason why the percentages of different type of adopters – innovators, early adopters etc. – would be the same for all new products and technologies. Therefore, they plead to use more general and flexible diffusion models to analyze adoption. Note that estimating potential market size in advance presents another complication in distinguishing different adoption groups.

[3] With respect to the adoption of innovative (smart) energy systems to promote sustainable energy use, Noppers et al. (2016) shows that symbolic attributes – the degree to which innovations say something about the adopting person – provide a powerful explanation of the distinction between adopters and non-adopters.

Many technologies actually do follow the S-shaped pattern as depicted in Figure 1, but the exact shape of the S-curve (and possible asymmetries) differs among technologies. Unexpected changes in market demand, policy and regulation, component technologies, or complementary technologies can shorten or extend the lifecycle. Moreover, investors can actively influence the shape of the S-curve through the nature of their development, see for example Golder and Tellis (1997).

2.2. Modeling diffusion processes

Since the late 1960s, a large literature has emerged on modeling diffusion paths for new products and technologies, see Mahajan, Muller and Bass (1990) and Peres, Muller and Mahajan (2010) for detailed overviews. Generally speaking there are two broad approaches to model diffusion paths for new products and technologies. First, there is the “aggregate approach” to modeling diffusion. It implicitly assumes that the social system is homogeneous and adoption of a new product or technology is dominantly driven by consumer interaction, that is, by “word-of-mouth”. The seminal model in this line of research was introduced by Bass (1969) and has been modified and augmented in many ways since. In this model, the focus is on the total number of new adopters in a given period where all individual non-adopters at the time have an identical probability to adopt. The advantage of the approach is that it allows parsimonious modeling on a macro-level, requiring few data. The disadvantage is that it does not shed light on the underlying trade-off an individual makes when deciding to adopt or not and ignores the possible influence of individual factors in this decision.

Second, a more recent line of research recognizes the potential role of consumer heterogeneity and gives it a central role in the diffusion process. In this research individual agents optimize some utility or benefit function, conditional on a number of individual constraints and preferences and on product and technology characteristics, and possibly subject to uncertainty as well. Obviously, the probability to adopt then will differ across agents. Apart from allowing for adoption heterogeneity, the approach also has the advantage of allowing for interdependencies between agents through network effects and of allowing the analysis of spatial diffusion. However, the approach faces substantial challenges too. The utility function and decision rule need to be chosen and an aggregation procedure has to be constructed to translate the myriad individual decisions into a macro framework. Often this approach combines elements like multi-agent (Schwoon, 2006), complex system (Struben and Sterman, 2007) and game theory (Smit, 2003). Köhler et al. (2009) and Huétink, van der Vooren and Alkemade (2010) use agent-based modelling techniques as a framework for assessing possible pathways of the transition to a sustainable mobility society. Meyer and Winebrake

(2009) use system dynamics modeling to analyze the complementary vehicle-infrastructure relationships exhibited in a hydrogen transportation system.

2.3. Aggregate diffusion models

Aggregate diffusion models are used extensively in marketing, business studies, as well as policy research to provide forecasts of adoption (demand) for new (durable) consumer products as well as new technologies.[4] The models focus on the macro population level and are based on the overall statistical behavior of potential adopters. We start our discussion with the Bass model (Bass, 1969), which – together with its broad offspring – is the most widely accepted, used and cited model in the field (Mahajan, Muller and Bass, 1990). In the Bass model, the expected adoption of the new technology can be presented using a simple differential equation. For the moment, we use continuous time notation:

$$\frac{dK}{dt} = p[\overline{K} - K_t] + \frac{q}{\overline{K}} K_t[\overline{K} - K_t] = [p + \frac{q}{\overline{K}} K_t][\overline{K} - K_t] \qquad [1]$$

In equation [1], K_t refers to the number of adopters at time *t*, d(.) is the difference operator, and $\overline{K}$ equals the ceiling or potential amount of adopters for the given technology. The equation states that in a short period, a constant fraction *p* of the non-adopters is expected to start using the technology. In addition, new adoption depends on the amount of agents that already have adopted the new technology, governed by the expression $qK_t/\overline{K}$. This latter term captures the impact of the consumer interaction, or the network effect. Alternatively, the Bass model can be written as

$$y_t = \frac{dY}{dt} = [p + qY_t][1 - Y_t] \qquad [2]$$

where $Y_t=K_t/\overline{K}$. While equation [1] was expressed in absolute number of adopters, it should be noted that equation [2] is expressed in percentage adoption. Y_t is the – expected – cumulative percentage of adopters at time *t*, which will approach one as time evolves. The time derivative of Y_t, expressed as y_t, is the probability density function, representing the instantaneous likelihood of purchase at time t. It is only based on the two diffusion parameters *p* and *q*, and on $(1-Y_t)$, the percentage of non-adopters at time *t*. In the literature, *p*

[4] A recent application in the energy field is Shin et al. (2016), who use a diffusion model to forecast demand for carbon capture and storage (CCS) technology.

is typically referred to as the “coefficient of innovation” or the “external influence”. It gives the proportion of the current non-adopters that will switch to the new technology per unit of time, independent of the current adoption success. In the standard Bass model, p is assumed to be constant. The parameter q is generally referred to as the “coefficient of imitation” or the “internal influence” and is assumed constant as well. It captures the communication or network effect in the adoption process.[5] It can be easily shown that both equation [1] and equation [2] have a closed-form solution.

Using the elegant and successful Bass model as a starting point, the literature shows an impressive proliferation of extensions and refinements. We refer to Easingwood, Mahajan and Muller (1983) for an overview of early day diffusion model characteristics. On the one hand, a number of approaches simplify the Bass model by assuming the coefficient of innovation p to equal zero, see for instance Fisher and Pry (1971). On the other hand, the literature criticizes the Bass model for being too restrictive in its assumptions itself. Easingwood et al. (1983) point out that the Bass model is quite rigid in assuming i) the parameter q to be constant regardless of the degree of penetration arrived at already, ii) confining the inflection point of the S-curve – that is, the point at which the rate of adoption is highest – to be below but close to 50%, and iii) assuming a perfectly symmetric diffusion pattern before and after the inflection point. In their view, this puts severe limits on the applicability of the Bass model. As an alternative, Easingwood et al. (1983) propose a logistic diffusion model – labeled a non-uniform influence (NUI) model – which leads to equation [3]:

$$y_t = \frac{dY}{dt} = [p + qY_t^{\delta}][1 - Y_t] \qquad [3]$$

When δ equals one, the model converges towards the Bass model. However, for δ not equal to one, different diffusion paths arise with a time-varying coefficient of innovation, and faster or slower adoption depend on the value of δ and asymmetric effects. If $0 < \delta < 1$, it causes an acceleration of influence leading to an earlier and higher peak. If $\delta > 1$, it causes delay in influence leading to a lower and later peak. In empirical applications both examples of high and low δ values are found. In Easingwood, Mahajan and Muller (1981), this logistic model is used in restricted form with $p=0$ to allow for a convenient closed-form solution.

[5] Technically, the sum $p + q$ controls scale and the ratio $\frac{q}{p}$ controls shape. Note that the condition $\frac{q}{p} > 1$ is necessary for the diffusion curve to be S-shaped as in Figure 1.

Another line of criticism focuses on the lack of attention in the basic Bass model for underlying economic drivers of the adoption process. The Bass model imposes a semi-automatic process where only the previously achieved degree of adoption can influence the probability of new adopters. However, from an economic perspective one would expect marketing effort and price to be important determinants of the speed at which agents are willing to adopt a new product or technology. Moreover, the same factors could also have an impact on the market potential. In terms of the Bass model, *p*, *q* and $\overline{K}$ all could be functions of such drivers. Examples of models that endogenize market potential $\overline{K}$ are Kalish (1985) and Kamakura and Balasubramanian (1987). Horsky and Simon (1983) are a good example of modeling the probability of adoption as a function of marketing effort. Bass et al. (1994) provide an extended overview of diffusion models that include price and/or advertising as economic fundamentals.

In an attempt to integrate the above criticism into the standard Bass framework, Bass et al. (1994) propose the GB model. It is a generalization of the basic Bass model which on the one hand allows the inclusion of decision variables (such as price and advertising) and on the other hand maintains the basic shape of the diffusion curve. The GB model has the following form:

$$y_t = \frac{dY}{dt} = [p + qY_t][1 - Y_t]x_t \qquad [4]$$

where x_t may be a function of decision variables such as marketing effort and price. Note that equation [4] can be easily rewritten as follows:

$$y_t = \frac{dY}{dt} = [px_t + qx_tY_t][1 - Y_t] = [p^*(x_t) + q^*(x_t)Y_t][1 - Y_t] \qquad [5]$$

Equation [5] again looks like the basis Bass model with parameters *p** and *q** which are functions of x_t. The main difference is that these two parameters now are time-dependent functions of one of more economic drivers potentially. Compared to other models that directly model the impact of economic decision variables on the adoption rate, Bass et al. (1994) have imposed the extra restriction that *p** and *q** have exactly identical time-dynamics, given by x_t . Theoretically, there appears to be no clear reason why one would assume the rate of innovation (*p**) and the rate of imitation (*q**) to respond similarly to changes in price or advertisement.

Bass et al. (1994) operationalize x_t as follows:

$$x_t = 1 + \beta_1 P_t^{'} + \beta_2 A_t^{'} \quad [6]$$

where *P* is price and *A* is marketing effort (spending). Then, $P_t^{'}$ is the rate of price change and $A_t^{'}$ the rate of change in advertising spending at time *t*. The GB model has the appealing property that both price and advertising can be incorporated in the diffusion process, while still allowing the model to reduce to the basic model in case the rate of change of *P* and *A* are approximately constant. Actually, Bass et al. (1994) claim the basic Bass model works so well in many applications because the price and advertisement development is rather smooth so that parameters *p* and *q* can capture the effect of economic drivers on the rate of adoption.

Obviously, the GB model has general potential and can be applied to a wide range of innovations. In this paper, we provide an illustration by applying it to the case of the introduction of infrastructure for hydrogen cars in the Netherlands. Using a simulation analysis, we focus on the consequences of incorporating the interdependence between the development and the roll-out of a hydrogen infrastructure and the adoption of hydrogen cars by consumers for the investment decision in infrastructure.

3. An application to the case of hydrogen infrastructure in the Netherlands

In this section, we first introduce the setup of the hydrogen infrastructure project in the Netherlands, see also Engelen et al. (2016). Subsequently, we develop and discuss the way we adapt the GB model to this particular case. In particular, we show how we model the sensitivity of hydrogen cars to available hydrogen infrastructure.

3.1 Description of the hydrogen infrastructure project

The setup of the hydrogen infrastructure project is loosely based on the EU HyWays (2008) project. It lays out a phased roadmap for hydrogen stations in 10 European countries, viz. Finland, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, Spain, and the United Kingdom (HyWays, 2008). This hydrogen energy roadmap distinguishes the following four settings with respect to policy support and technical learning: ‘baseline’, ‘modest policy support and modest learning’, ‘high policy support and high learning’, and ‘very high policy support and high learning'. Here, we take the 'modest policy support and modest learning' setting as our starting point.

Furthermore, the roadmap assumes a number of stages. Phase I (2010-2015) is a small scale experimental (pre-commercial) phase which brings up to 10,000 hydrogen vehicles on European roads. Phase II (2015-2020) is the early commercial phase. The roadmap assumes that in the early commercial phase, three to six early user centers will be developed in each country. For the Netherlands, these are the regions around Amsterdam, Rotterdam and Nijmegen (see Engelen et al., 2016 for an application on a regional scale). The ambition is to link these national centers through so-called hydrogen corridors. Subsequently, national-wide networks will be rolled out. With respect to the number of required stations, the HyWays roadmap assumes that in the early commercial phase about 400 stations will be necessary in the early user centers plus another 500 to facilitate the hydrogen corridors. In the full commercialization stage III an increase is foreseen to 4 million between 2020 and 2025 and to 16 million hydrogen cars after 2025. In the final stage after 2025, 13,000 to 20,000 stations ultimately will be needed to serve ten million hydrogen vehicles.[6]

All of the above numbers are for the total of 10 participating countries, so we need to scale those numbers to obtain estimates for the Dutch market. When measured in terms of the number of users, the Netherlands account for 3.34% of the total target population in the EU, while measured in kilometers of roads they account for 3.95% of the EU total (Stiller et al., 2008). Taking 4% as the approximate proportion of the Netherlands within the HyWays project, this would correspond to 400 hydrogen cars by 2015, 20,000 cars by 2020 and a further growth to 640,000 after 2025. With respect to the number of stations, the HyWays setup implies that about 30 stations would be built by 2015 and 800 by the end of phase III. At the end, there would be 800 stations in the Netherlands serving about 640,000 cars.[7]

The timing of achieving those target numbers is dependent on the specific setting underlying the scenario. In our analysis we take a 34 year horizon. In our analysis, we choose the pre-commercial phase I to run from 2010 until 2014. It is comprised of technology refinement and market preparation. The early commercialization phase II is from 2015 until 2024 and the full commercialization phase III from 2025 until 2044. In the real option analysis, we use a proxy

[6] The roadmap also assumes the size of the stations to increase over time, from single dispenser stations in the early phases to large multiple dispenser stations later on. In our analysis, we abstract from this complication.

[7] In reality, the objectives of the HyWays scenario have not been realized so far and the project considerably lags behind the 2008 expectations. We nevertheless use its assumptions and original time path for the setup and simulations in this paper.

for the cash flows after 2044. Subsequently, we design six different strategies with respect to the timing of investment in infrastructure, leading to different speeds of construction for the refueling stations. In all scenarios, the final number of 800 stations is reached in 2044. Furthermore, we assume demand (adoption) to be governed by a Bass model. In the basic Bass model where the number of available stations rises linearly from zero to 800 in 34 years, the number of users in the Netherlands is estimated to be about 15,000 in 2014 and to slightly increase above 200,000 by 2024 to approach 640,000 in 2044.

For some intuition behind these different phases, consider the following. Generally, the introduction of an innovative technology leads to early adoption by enthusiasts. In this case, the pre-commercialization phase would be attained when enough hydrogen stations are in place to satisfy the refueling needs of many early adopters. These consumers will be somewhat more willing to be inconvenienced by driving out of their way to refuel with hydrogen. Early-commercialization phase is attained when enough hydrogen stations are in place to satisfy a larger portion of the general population. High volume sales to the general public take place in the final full-commercialization phase. Since many consumers want to be able to drive long distances and do not want to be confined to a specific area, a local infrastructure probably will not suffice in this stage anymore. To overcome range anxiety, at least a coarse national network would have to be in place.[8]

The advantage of a multi-phased process is that it allows staged investments and investment decisions. Moreover, it makes a real option analysis an attractive and appropriate approach to assess the attractiveness of the investment. Each stage can be viewed as an option on the value of subsequent stages and valued as a compound option (Cassimon et al., 2004). It is important to note that phase III (full-commercialization) cannot proceed without the execution and successful completion of phase II, which itself will only take place upon the successful transition from phase I. The end points of phases I and II thus represent decision times, in addition to the starting decision at the beginning of stage I for the investor in hydrogen infrastructure. A positive continuation decision at that time requires the option value of the future project to exceed the extra investment required to enter the next phase. If not, the project will be terminated.

To calculate the expected operating cash flows for each project phase, we need to estimate the present value of the expected operating revenues R_t less operating expenses C_t, which requires a substantial amount of assumptions with respect to the input values of all parameters of the

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[8] Similar developments are seen in the electrical vehicles market.

cash flow model. To calculate hydrogen demand for fuel cell passenger vehicles, we assume that each vehicle will use approximately 0,7 kg of hydrogen each day, amounting to 255,5 kg per year. For an average fuel cell vehicle with a fuel economy of 80 to 96 kilometer per kg, this would accommodate about 56 to 64 kilometer of driving on an average day (Ogden, 1999; CaFCP, 2008). For hydrogen fuel to be competitive with fossil fuels, the literature generally assumes a retail price of €10/kg (van Benthem, Kramer and Ramer, 2006).[9] Although hydrogen is much cheaper produced from natural gas, the production process is always associated with the emission of greenhouse gases and local pollutants (Haryanto, Fernando, Murali, Adhikari, 2005). Sustainable hydrogen cost is initially about €5/kg (phase I) , but due to technical learning, we assume it will gradually decrease to €4/kg in phase II and a long-term production cost of €3,4/kg in phase III (adapted from Lebutsch and Weeda, 2011 and van Benthem et al., 2006). This includes all the relevant expenses, for instance, transportation to the refilling station and carbon capture and storage (CCS) costs if necessary. After 2044, annual operational cash flows are assumed to remain constant forever. Their present value in 2044 is used in the computations as the residual value of the investment.

For the computations, we furthermore use a 25,5 percent marginal tax rate (KPMG, 2011), an average Eurozone inflation rate of 2,24% (ECB, 2011), a 1,13% real interest rate, a 21,21% net working capital requirement in a given year (as percentage of the sales) (Damodaran, 2011) and a straight-line depreciation over the 20 year economic life of each station. We use a risk adjusted discount rate of 8% for calculating the NPV of the project cash flows.[10]

Each stage also requires investments in the necessary amount of hydrogen fuel stations in order to operate the fuel network. The cost of a hydrogen fuel station depends upon many factors, including the type of station, location, equipment manufacturing volume and continuing technology advancements. Here, we base our assumptions on Lebutsch and Weeda (2011). We assume a standard hydrogen station initially costs €0,95 million. Unit investment costs will decrease over time as a result of economies of scale and learning. To reflect this, we specify the cost function as $\varpi(N) = \alpha \cdot N^{-b}$, where $\varpi(N)$ is the investment cost of the N^{th} unit, b is a learning parameter and α the investment cost of the first unit (€0,95 million). We choose b to be equal to 0,0465, so that the unit costs decrease to €0,70 million by 2044. The

[9] We take into account the regular fuel taxes in the Netherlands such as excise duty and VAT, which lowers the net retail price to €4/kg.

[10] This cost of capital corresponds to the 2010 sector averages of oil and gas distribution (7,19%), environmental (7,62%), natural gas (8,07%), power (8,23%), automotive (8,58%) and chemical (8,88%). Numbers are taken from Damodaran (2011).

average investment cost to build N fuel stations will therefore be equal to $I = a \cdot \int_{1}^{N} N^{-b} dN$.

Fixed one-time installation costs amount to 30 percent of the unit costs and annual maintenance costs are 3,5%. Additional labor costs are €0,5mln per year.

3.2. The Model

In our application, we will start from the GB model in equation [4]. However, rather than assuming that x_t is a function of price and marketing effort, we assume x_t is a function of availability of refueling stations. Put differently, we hypothesize that potential buyers of a hydrogen car – adopters of the new hydrogen technology – will be more inclined to actually buy the car when they know there will be sufficient refueling stations in the region they intend to drive the car. Specifically, we propose

$$x_t = 1 + \beta \frac{N_t - \overline{N}_t}{\overline{N}_t} \qquad [7]$$

where N_t equals the cumulative number of refueling stations that has been built up till year t and $\overline{N}_t$ equals the cumulative number of refueling stations that would have been built up till year t when the same amount of stations would be built every year over the complete 34 year planning horizon. The gap in equation [7] then indicates how far the actual building – investment – strategy deviates from the constant investment path. Note that when actual investment exactly follows the linear trend, the gap will be zero and x_t will equal one for the whole period. In this “neutral” scenario, the model reduces to the basic Bass model, consistent with the argument of Bass et al. (1994).

Further, we define β as the diffusion coefficient that controls the effect of available stations in accelerating and decelerating the diffusion process. The motivation behind this setting is to reflect the importance of refueling infrastructure investments on the market penetration of hydrogen cars. When β equals zero, the sensitivity of adoption to realized stations is zero and the model reduces to the standard Bass model. The higher β, the stronger the effect of early investment on adoption will be. We will use the combination of equations [1], [4] and [7] in our scenario analysis, using different paths for N_t and different parameter values for β. The overall equation than looks as

$$\frac{dK}{dt} = [p + \frac{q}{\overline{K}} K_t][\overline{K} - K_t] * [1 + \beta \frac{N_t - \overline{N}_t}{\overline{N}_t}] \qquad [8]$$

4. A Scenario Analysis

Direct estimation of a simple Bass model or an extended GB model for the hydrogen case is infeasible, due to the lack of actual data on infrastructure investment and consumer adoption. This is similar to many previous disruptive technologies prior to market entry (Hardman, Steinberger-Wilckens and van der Horst, 2013). For that reason, we focus on a scenario analysis.

As discussed previously, we assume that the rollout of an infrastructure for hydrogen fuel cell vehicles will cover the period 2010-2044. In these 34 years, we assume 800 fueling stations will be built to service a maximum capacity of 640,000 vehicles ($\overline{K}$). However, the timing of the building process is taken as a free parameter here. The purpose of the scenario exercise is to investigate the impact of different speeds at which the stations are built on the potential profitability of the overall project, taking into account the impact of the building strategy on the adoption speed of hydrogen cars in the market.

We do this by embedding the GB model of equation [8] into the real option framework. In the following section, we define six plausible investment scenarios, distinguished by the speed at which refueling stations are built. The GB model pins down the diffusion process of adoption through three parameters p, q and β. For p and q we use constant values across all scenarios, calibrated on the HyWays (2008) characteristics. For β we use four different parameter values, reflecting different demand sensitivities with respect to the availability of infrastructure. The higher β, the more weight potential users attach to having easy access the refueling infrastructure in their adoption decision. The results will shed light on the way the optimal investment (building) strategy depends on the sensitivity of adoption to available infrastructure.

4.1. Scenario assumptions

We take a two-step approach. First, we motivate the six different scenarios. Subsequently, we elaborate on the choice of p, q and β.

We start from the so-called ‘neutral’ scenario – henceforth labeled *Neutral*. This is the base scenario in which the stations are built at constant speed over the whole 34 year period. It is constructed as a neutral, steady increase scenario. That is, every year about 24 stations (=800/34) are added to the existing stock of stations. It follows from equation [8] that in the ‘neutral’ scenario the diffusion process will take the typical S-shaped Bass distribution. In this case the gap variable in x_t is zero throughout the whole period regardless of the value of β, because the investment gap $\frac{N_t - \overline{N}_t}{\overline{N}_t}$ is zero.

Subsequently, we design a number of other scenarios in which the building speed differs from *Neutral*.[11] Four scenarios follow a similar pattern, with a linear (constant speed) build-up until 2024 and a second linear path between 2024 and 2044. *Cautious* has a very slow start with only 50 stations built in the first fourteen years. As a result, building speed has to pick up substantially to build the remaining 750 stations between 2025 and 2044. In *Conservative* the number of stations built in the first fourteen years doubles to 100 (compared to *Cautious).* In *Confident*, again a doubling takes place, to 200 in the first fourteen years. Note that all of these scenarios still build at a lower speed initially than *Neutral.* In *Neutral*, 329 stations are built between 2010 and 2024. *Aggressive* is the mirror image of *Confident* relative to *Neutral.* In *Aggressive*, 460 stations are built in the first fourteen years which is as much more relative to *Neutral* as *Confident* is less. Finally, *Catch*-up starts with the same speed as *Confident*, but accelerates after ten years (in 2020) until it reaches the level of *Aggressive* in 2034 where it slows down again to follow the latter path.[12] Table 1 provides an overview of the build-up per scenario.

[11] Obviously, an infinite number of scenarios is possible. We have chosen a grid that allows to bring out the most important conclusions.

[12] The building strategy in the *Conservative* scenario roughly equals that of HyWays (2008).

Scenario	Timing of the build-up (in new stations per period; in each period, the build-up is linear)					
	Period 1-34	Period 1-14	Period 14-34	Period 1-10	Period 10-24	Period 24-34
Neutral	800	(329)	(471)	(235)	(330)	(235)
Cautious		50	750			
Conservative		100	700			
Confident		200	600			
Aggressive		460	340			
Catch-up				143	487	170

Table 1 Building speed per scenario and regime (new stations per year)

Note that the regime changes in the different scenarios do not necessarily coincide with the decision years 2014 and 2024 in the real option analysis. However, we will evaluate all scenarios on the basis of these decision points for the infrastructure developer. Figure 3 provides a graphical illustration of the different investment strategies and corresponding growth of the number of refueling stations in the different scenarios.

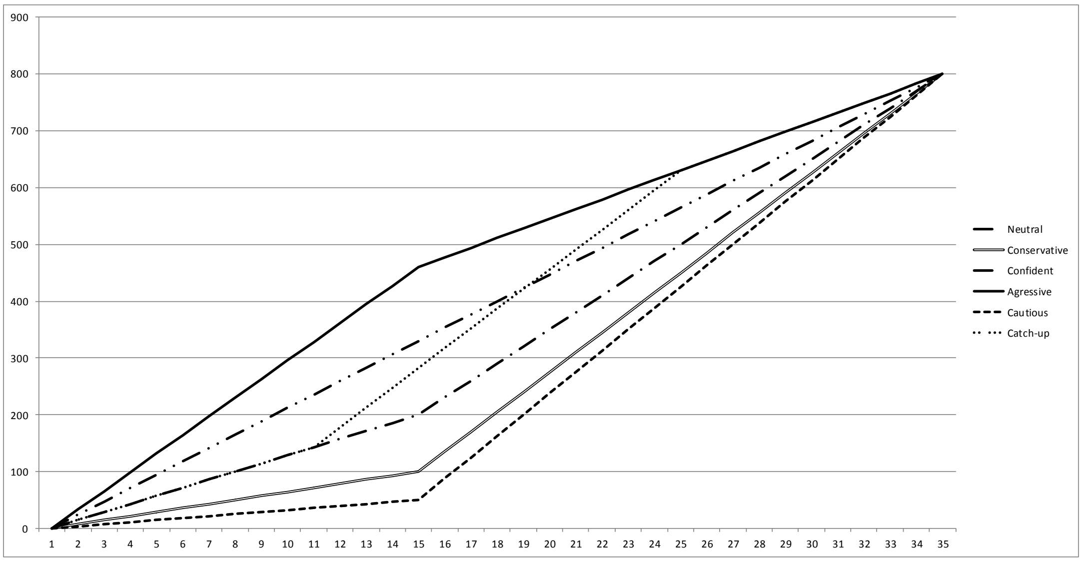

Figure 3 Number of Stations in Each Scenario

We now turn to the parameterization of the model. Obviously Bass type models have been used extensively in the literature to model the diffusion of new products and technologies.

Especially for consumer durables many empirical applications are available, see for example Bass et al. (1994), Easingwood et al. (1983) and Srinivasan and Mason (1986). Estimates for p typically are in the range from 0 to 0.04, while estimates for q range from around 0.20 to about 0.70. In some applications the ceiling $\overline{K}$ is pre-specified, in others it is estimated as an extra parameter. Estimation methods include simple OLS, Maximum Likelihood Estimation (MLE) and non-linear least squares (NLS). We refer to Srinivasan and Mason (1986) for a comparison and discussion. Moreover, estimation typically requires reformulating equation [1] or [8] in discrete time. The discrete version of equation [8] looks as follows

$$dK_t = K_t - K_{t-1} = [p + \frac{q}{\overline{K}} K_{t-1}][\overline{K} - K_{t-1}] * [1 + \beta \frac{N_{t-1} - \overline{N}_{t-1}}{\overline{N}_{t-1}}] \qquad [9]$$

It allows for the estimation of 4 parameters, p, q, β and $\overline{K}$ .When β is set to zero, the model reduces to the standard Bass model with three parameters to be estimated.

We calibrate the parameters p and q in equation [9] at 0.025 and 0.275 to allow the diffusion process to converge gradually towards the potential adoption level $\overline{K}$ (640,000) by the year 2044. These values fall into the range usually found when estimating the Bass model. For β we choose four different values reflecting differences in the sensitivity of demand to the availability of refueling stations using the GB model. In particular, we consecutively set the value of β equal to zero, 0.25, 0.50 and 0.75. When β equals zero, the number of available refueling stations plays no role in the consumers' decision to adopt the new technology and the GB model reduces to the standard Bass model. The higher the value of β, the more important the availability of sufficient refueling stations is for consumers.

4.2. Results

For each combination of a specific scenario and a value of β, we now can compute the adoption speed and corresponding demand for hydrogen vehicles. From this, the time path of costs and revenues and operating cash flows can be computed. These in turn serve as input for the computation of the net present values for each stage as well as the real option value at the start of the project. The results of this exercise are reported in Tables 2-5. Each table corresponds to a different value of β. The results for scenario *Neutral* are identical across β values as the investment gap equals zero all the time.

We start with the case of β =0, where infrastructure availability does not influence adoption speed. Essentially, the GB model reduces to the basic Bass model and adoption only is a function of the parameters p and q. As a result, all scenarios are equal on the revenue side.

However, the different scenarios do differ in the speed at which stations are built and, thus, in the time path of cash outflows. The results are provided in Table 2. The first three columns of Table 2 contain the net present values for each investment phase in present value terms: phase I is between year 1 and year 4, phase II is between year 5 and year 14, and phase III is between year 15 and year 34. Column 4 sums these NPVs and gives the overall NPV of the project at its start. According to the NPV criterion, a minimum condition for the project to start is a positive NPV. Column 5 has the real option value of the project today.[13] According to the real option criterion, the project is feasible when the call option value today exceeds the initially required net investment. We assume this equals the NPV of Phase I operating cash flows in present value terms. The *Project Value* in column 6 equals the call option value minus the cash flows (required investment) from phase 1. That is, a positive project value implies the option is "in-the-money" and can be exercised to start the project.

A first thing to note from Table 2 (the case of β =0, where infrastructure availability does not influence adoption speed) is that the NPV analysis results in rejection of the project, regardless of the specific time path of investments. This is a common result for large infrastructural projects as uncertainty about future revenues is large and upfront investment outlays are high. From a NPV perspective no infrastructure developer will start the current hydrogen project. This is exactly the reason why real option theory provides an attractive alternative in project assessment. Table 2 shows that the option criterion only rejects the project in the most risky scenario, *Aggressive*. The scenarios in which investment starts very slowly do best. This result is not surprising. Since demand (adoption) is insensitive to the availability of infrastructure (β =0), aggressively and quickly building many stations in the early years does not pay off. It leads to high costs without compensating revenues. Slow investment in the early years reduces costs in the first phase, as can be seen by comparing the Phase I NPV across scenarios in column 1. It puts the scenarios where investment starts more aggressively at a disadvantage.

Tables 3 to 5 have the same design as Table 2 and provide information on the role of higher sensitivity of demand to available refueling stations. In Table 3, β rises to 0.25, suggesting consumer demand is somewhat sensitive to the availability of refueling stations. It remains true that the project would be rejected on the basis of overall NPV, but will be accepted using real option valuation regardless of the specific building design. In terms of project value, the scenarios converge a bit. Especially the two slow scenarios (*Cautious* and *Conservative*) now have a substantially lower project value, while the project value for *Aggressive* increases

[13] As the infrastructure project is a multi-stage investment, we use the n-fold compound option model of Cassimon et al. (2004) to compute the real option values.

somewhat. These effects are due to the fact that the faster building scenarios now benefit on the revenue side from faster adoption compared to the slow building scenarios. However the impact is insufficient to alter the ranking of the projects substantially. Only *Confident* and *Catch-up* change places.

When demand sensitivity rises even more with a β of 0.5, we do see somewhat more of an effect. Table 4 shows that with this value of β, the scenarios actually converge considerably in overall performance. Differences both in overall NPV and in Project Value are relatively small. *Catch-up* actually shows the best performance. In Table 5, we provide evidence for the case when demand sensitivity is high ($\beta=0.75$). Now, *Cautious* and *Conservative* make up the rear. Actually, the project is rejected for *Cautious* and only marginally accepted for *Conservative*. Since *Conservative* is the scenario which we derived from the Hyways case, it deserves attention on its own. Interestingly it does quite well when there is low demand responsiveness to the availability of infrastructure, but falls to the bottom of the rankings when demand responsiveness increases.

In this particular setup, the consequences of failing to correctly incorporate the endogeneity of demand in the analysis in terms of inappropriately accepting or rejecting the project at the start are limited. Taking the β=0 scenario as our benchmark, the results show that with relatively strong demand responsiveness, *Aggressive* may be incorrectly rejected, while *Cautious* may be incorrectly accepted – and even deemed optimal. The project is accepted on the basis of the real option value for all other scenarios for all values of β. However, there is no guarantee decisions would also turn out this way.

Overall, our analysis shows it is important to understand and appropriately model the diffusion process of a new technology like the development of hydrogen- vehicles and the corresponding infrastructure. Ignoring the potential interaction between the speed with which the required infrastructure – and for that matter also a sufficient set of attractive vehicles themselves – will become available and the adoption process may lead to suboptimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general.

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-24	-53	76	0	169	145	Invest	1
Conservative	-37	-77	91	-23	161	124	Invest	2
Confident	-64	-124	119	-69	149	85	Invest	3
Aggressive	-130	-241	187	-184	128	-2	**Reject**	6
Catch-up	-64	-164	141	-87	148	84	Invest	4

Table 2 Comparing scenarios for β=0

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-22	-43	14	-51	123	101	Invest	1
Conservative	-36	-69	41	-64	125	89	Invest	2
Confident	-63	-119	91	-91	129	66	Invest	4
Aggressive	-131	-247	211	-166	145	14	Invest	6
Catch-up	-63	-159	121	-102	133	70	Invest	3

Table 3 Comparing scenarios for β=0.25

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-21	-36	-62	-119	69	48	Invest	2
Conservative	-35	-62	-18	-116	83	48	Invest	2
Confident	-62	-114	61	-116	108	46	Invest	4
Aggressive	-131	-253	233	-152	159	28	Invest	6
Catch-up	-62	-155	100	-117	121	59	Invest	1

Table 4 Comparing scenarios for β=0.5

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	2
Cautious	-20	-31	-150	-201	13	-7	**Reject**	6
Conservative	-34	-58	-86	-178	38	4	Invest	5
Confident	-62	-110	28	-144	86	24	Invest	4
Aggressive	-132	-260	251	-142	170	38	Invest	3
Catch-up	-62	-152	79	-134	106	44	Invest	1

Table 5 Comparing scenarios for β=0.75

5. Conclusions

In this paper, we explicitly incorporate the impact that realized investment in new infrastructure may have on adoption speed in a real options framework for investment decisions and analyze the consequences of this interdependence for optimal investment. The issue has the characteristics of a chicken-egg problem: without sufficient infrastructure, consumers will not adopt the new technology; but without (likely) adoption, investors will not build the infrastructure. To address the issue of choosing an optimal investment path when adoption depends on previous investments in the necessary infrastructure, we combine a real option modeling approach with a modified Generalized Bass model for the adoption diffusion process.

As an illustration, we apply the combined model to the case of the introduction of infrastructure investments for hydrogen- cars in the Netherlands. We perform a scenario analysis where we combine six different investment strategies with four different parameterizations of the GB model. We assume that the number of available re-fueling stations – relative to a linear trend – is a key driver of the diffusion model that captures the adoption decision. The variation in parameterization captures different degrees of demand sensitivity to existing infrastructure.

Our results show that it is important to understand and appropriately model the diffusion process of a new technology like the development of hydrogen- vehicles and the corresponding infrastructure. Ignoring the potential interaction between the speed with which the required infrastructure – and for that matter also a sufficient set of attractive vehicles themselves – will become available and the adoption process may lead to suboptimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general. More research is needed to obtain realistic estimates of the magnitude of the relevant parameters that govern the adoption diffusion process for new technologies. This is left to future research.

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