CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2021

2nd Conference on Production Systems and Logistics

Application Of Innovation Diffusions Models In Factory Planning For Fuel Cell Systems

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Abstract

The planning of factories and production processes is subject to constantly changing requirements and has always been challenged by uncertain future forecasts. Factory planning projects initiated for the production of innovative products are particularly affected. For these products, there is almost no historical or empirical data available, so the forecasts can only be based on estimated influencing variables and data from similar products. Accordingly, the risk that the selected capacity does not match the actual market demand is higher. While the capacity of a factory represents a long-term investment decision, the spread of innovations can fail within a short timeframe or occur far below the expected level. For this reason, it can be assumed that insights from innovation research offer a planning advantage in forecasting the production potential. Regarding an increasing number of global product innovations, the evaluation of empirical data by means of suitable models and methods is becoming more and more accurate in order to reflect typical market patterns based on recurring customer behaviour. This paper takes up these trends and proposes an approach how innovation metrics can be included in the capacity dimensioning process of factory projects. For this purpose, the BASS diffusion model is used to realistically map different market scenarios for the required capacity curves.

Keywords

Factory Planning; Innovation; Diffusion; Capacity Dimensioning, Fuel Cell

1. Introduction

The market for fuel cell systems for vehicles in Germany and Europe is currently still relatively small, especially in comparison with North America and Asia [1]. It is generally assumed that this will change in the near future [2]. Indications of this, are the ambitious German national hydrogen strategy [3] and the EU Hydrogen Strategy [4]. Trencher and Edianto show that there is consensus in industry and research that those policy signals are drivers in market development [5]. In order to drive forward the transformation of energy supply towards fewer emissions, fuel cell technology is well suited, especially in areas where it is otherwise difficult to electrify applications. One of these applications are utility vehicles where fuel cell systems are generally better suited than battery electric systems [6]. Hence, within this article, the focus will be on utility vehicles like trucks and buses.

The future market size, and therefore the sales potential of a company, in a timeframe of five to ten years and beyond is subject to great uncertainty. This influences companies' factory planning. In the worst case, factory planning is based on very optimistic estimates, while the technology remains a niche application or is substituted by other technologies. When focusing on the mobility sector one competing technology is the battery electric vehicle (BEV). In comparison to fuel cell electric vehicles (FCEVs) BEVs are some years ahead in terms of technological maturity and cost reductions [5]. It is expected, that this gap in economic competitiveness will close in the coming decade, even for light-duty vehicles [7]. These forecasts are not certain and rely on continuous technical improvement, which, however, cannot be guaranteed.

In 1998, a miscalculation of future demand and corresponding capacity cost Siemens about $150m [8]. When the decision to invest in a chip plant in Tyneside (UK) was made in 1995, Siemens predicted high demand for 16Mb chips and constant prices. Due to a sharp drop in prices (95% between 1995 and 1998); Siemens was forced to close its plant in Tyneside. This misjudgement was due to an incorrect assessment of the cycles of the traditionally fluctuating demand in the semiconductor industry [9]. Such errors are financially very difficult or even impossible to bear, especially for small and medium-sized companies.

Especially factory and production process planning for innovative products, such as fuel cell components, face the challenge of accurate forecasts because historical or empirical market data do not exist. This leads to a higher risk that capacity and demand do not match, which can lead to expensive adjustment measures.

To mitigate the risk of a capacity and demand mismatch, we suggest incorporating insights from innovation research into traditional factory planning methods with particular focus on capacity dimensioning. For this purpose, this paper presents a short introduction to capacity dimensioning methods and diffusion models. Chapter 4 presents a linkage of both domains concerning the factory planning for the assembly of fuel cell stacks. Chapter 5 compares the advantages and disadvantages of the proposed method. The paper concludes with a summary of the previous points and suggests future research activities on the topic.

2. Capacity Dimensioning

Several authors have developed structured overviews on standardized stages and steps of the factory planning process [10,11]. Moreover, the specific planning requirements and contents are formalized and described in the norm VDI 5200 [12] by the German Society of Engineers which also refers to the official scale of fees for services by architects and engineers (HOAI [13]). Based on these documents, the planning and estimation of required capacity can generally be seen as a base for subsequent structure planning. When investigating these aspects in more detail it seems useful to distinguish between the terms capacity dimensioning and capacity planning to avoid confusion. While the main objective of the latter is the optimal allocation of a fixed capacity according to cost criteria, delivery reliability or flexibility [14], the capacity to be dimensioned refers to the strategic orientation of serving a forecast customer demand without gaps and also in compliance with overall corporate objectives [15]. Accordingly, capacity dimensioning can be interpreted as a discipline of factory planning, the subject of which is the balancing between an order quantity (capacity requirement) and the output quantity achievable through production factors (available capacity).

Major disadvantages of these sequential procedures are information losses on the interface between different planning partners who are, for instance, responsible for production infrastructure, HVAC and plumbing. Furthermore, it leads to an additional effort caused by iterative decision processes. As an answer to this, several concepts for integrated factory planning were developed and refined. An exemplary methodological framework is presented by Wiendahl et al. [11] with the so called synergetic approach to factory planning which comprises a two-dimensional project planning concept that relies on early cooperation between construction planning and production planning. Consequentially, the aspired cooperation necessitates a consolidated base for the planning and construction operations. With regard to this, the methodological and software-related framework of Building Information Modeling (BIM) serves as a basis for collaboration. The associated XML-based and openBIM-oriented scheme, named Industry Foundation Classes (IFC), is currently oriented to the development of buildings and their infrastructure. Thus, this may provide the starting point for the conjoint modelling of the production facilities infrastructure as well as logistic elements.

In any case, a flexible and precise forecast of product demands for infrastructure dimensioning is necessary in order to design and build a flexible and future-oriented production facility.

The basis for planning is a quantification of future demand, which can be carried out using various forecasting methods. Depending on the application, Schönsleben [14] suggests a past- or future-oriented approach. The former is used if valid consumption data for the specific product can be accessed. These are transferred into time series and evaluated by means of mathematical or graphical procedures. If, on the other hand, such values are not available with the necessary validity, a forward-looking method can be used. A characteristic feature of these procedures is that available information on future demand trends is recorded and modelled as extensively as possible. In terms of methodology, both mathematical models and intuitive approaches, such as estimation based on empirical values, have become established. It should be emphasized that the resulting forecast data is subject to the limitations of the method used and therefore only partially addresses the complexity and interdisciplinarity of the influences on market demand.

The forecast results are then transferred into a formal production program which, in addition to the quantity data, also contains product-specific, value-based and time-relevant specifications [10]. At the same time, data for determining the available capacity must be prepared. This is limited by the technical performance of the available resources, and if necessary, personnel organization specifications and budget restrictions can also influence the available capacity [16]. With regard to this, it must also be taken into account which manufacturing processes can be considered for individual production steps and whether this will be accompanied by future replacement investments. The collected data constitutes the basis for the concept-planning phase of factory planning. The data is used for dimensioning the capacity and derived space requirements. More concretely, this phase consists of the sub-steps of the technological, temporal and organizational comparison between capacity requirements and available capacity [11]. First, the information recorded in the available capacity is concretized in terms of the production processes that are used and the required operating resources (machines, robots, tools). The choice of technology creates the necessary conditions to harmonize the temporal premises of the production system in the next step. In conjunction with the personnel requirements of the individual workstations, different shift system variants are created and compared based on qualitative as well as quantitative criteria. Taking into account production-reducing factors such as rework or failures, the existing net-working time T_{Mi} is calculated by multiplying the gross operating time T_{MGi} and the time utilization factor η_{Ri} [17]:

$$T_{Mi} = T_{MGi} * \eta_{Ri} \tag{1}$$

At the same time, the required occupation time on the individual work stations is to be determined in terms of planned volumes linked to product-specific parts lists [11]. As formula 2 shows, this results from the sum of the set-up time T_{Cji} and the total production time T_{Pji} of a period, which depends from the forecasted production volume x_{ji} and the processing time per unit t_{uji}.

$$T_{Ri} = \sum_{j=1}^{J} T_{Cji} + T_{Pji} = \sum_{j=1}^{J} T_{Cji} + \sum_{j=1}^{J} (x_{ji} * t_{uji}) \tag{2}$$

The quotient of occupancy time T_{Ri} and net-working time T_{Mi} ultimately leads to the number of operating resources or personnel required (n_i).

$$n_i = \frac{T_{Ri}}{T_{Mi}} \tag{3}$$

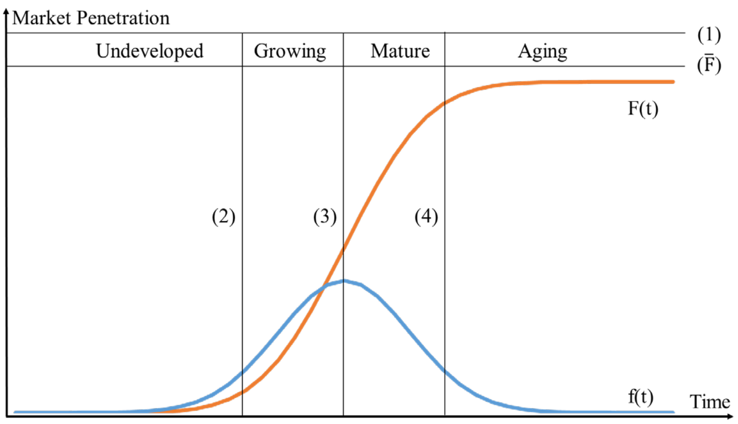
Since the demand forecast on the market does not usually follow an ideal, uniform course, the extent to which capacity should be adaptable in the future must also be taken into account. On the one hand, this concerns the provision of resource-bound flexibility (e.g. short-term changes in the shift model) [18], on the other hand, the strategic positioning in competition is decisive for the capacity expansion of the company.

General alternative strategies for this are *lead* (keeping excess capacity), *match* (demand-synchronous adjustment) and *lag* (delayed, risk-averse adjustment) [19]. The choice of strategy opens up the scope of action to shape the capacity decision depending on the product, the market environment and the company's goals.

The proven planning process shows that the demand forecasts collected at the beginning of the process consistently have a significant influence on the results of the individual steps. Accordingly, the demands for validity and realism are justified. This requirement is particularly challenging for innovative products and young markets. In these cases, it is typically uncertain whether the product will be able to successfully establish in the market and thus achieve market penetration. At the same time, typical competitive situations occur more frequently in young markets, which can strongly change the market distribution in the short term [20]. Since the typical forecasting methods reach the limits of their ability to depict these situations, innovation research has been dealing with the modelling of market developments for a long time. In combination with the capacity dimensioning process described above, these models can also help to consider product-typical demand trends in terms of capacity and to include changes in trends, for example due to specific innovation drivers, in planning at an early stage.

3. Overview of Innovation Diffusion Models

Innovation diffusion can be defined as “[…] the process by which an innovation is communicated through certain channels over time among the members of a social system” [21]. First popularized by Rogers in his 1962 published book *Diffusion of Innovations*, the theory became a staple in economics, social and communication sciences. The concept of innovation diffusion can be used on a micro level to describe the behaviour of individuals, but also on a macro level to describe how an innovation spreads across an entire social group or market. Rogers coined terms for five individual groups of innovation adopters and assumed that their distribution pattern corresponds to a normal distribution. Since then different authors suggested mathematical models to describe those patterns in detail. Figure 1 shows the general components of all diffusion models.



Symbol	Description
(1)	Whole Population e.g. of EU, China. Usually just a fraction of (1) are potential adopters $\bar{F}$
(2)	Lower threshold – if the adoption process reaches this level it will progress till completion
(3)	Infliction point – f (t) reaches its maximum, while the first degree derivative of $\bar{F}$ changes to negative
(4)	Upper threshold – adoption process is almost complete the rest of the adoption process cannot be exactly modelled
$\bar{F}$	Potential adopter population
F (t)	Cumulative adopter function
f (t)	Non-cumulative adopter function (diffusion function)

Figure 1: General components of diffusion models, based on [22]

Diffusion models are used to predict the sales of new technologies. Other methods, such as trend extrapolation, cannot be used because empirical values are not available. The use of diffusion models is thus classified as a future-oriented method for forecasting.

The project was intended to provide an initial proof of work of integrating diffusion models into capacity dimensioning. Therefore, to facilitate the validation of the results, only simple diffusion models were considered. These are usually based on the logistic distribution or derivatives thereof. Three of these models and their advantages and disadvantages will be briefly presented here.

- **Bass**
  Based on the work of Rogers, Bass extended the general model of different innovation stages with a mathematical foundation [23]. The Bass diffusion model turned out to be highly influential and is used in various industries to forecast future sales. This model replicates empirically proven progressions of the innovation course of products sufficiently accurately. Bass tested this himself using sales figures for 11 consumer products [23]. This model needs three different input parameters. Those are the coefficient of innovation (p), the coefficient of imitation (q) and the population of adopters (m). With sufficient data for the values p and q (e.g. from adoption processes of similar products), the model is generally very accurate. The model is less well tested for industrial goods [24]. However, see point 4 for an overview of comparable publications in which the Bass model was used to forecast similar technologies.
- **Fisher-Pry**
  The Fisher-Pry model makes three assumptions. First, it assumes that one technology is substituted by another to satisfy the same need. Second, if the substitution process reaches a certain threshold, then the process continues until full substitution occurs. Third, the substitution rate is proportional to the remaining quantity of the old product compared to the new one [25]. The model is characterized by its ease of use. To utilize it, only two input parameters need to be determined. One is the growth rate at the beginning of the diffusion process and the other is an estimate of the year in which the market penetration will be half [24]. However, compared to the Bass or Blackman-Mansfield models, the model yields less meaningful results [24].
- **Blackman-Mansfield**
  In itself, Blackman's model does not represent a diffusion model. In contrast to the models mentioned so far, it does not examine the substitution or adoption of a product, but the development of the performance of a technology, expressed in a figure of merit [26]. However, Blackman, who bases his model on the work of Mansfield [27], himself shows the connection between technical progress and market substitution [26]. Compared to the Bass model, the factor of cost between different technology options is considered, which can be an advantage [24]. However, the model produces overly optimistic values at the beginning of the prediction and overly pessimistic values at the end [22].

As indicated earlier, the models shown here represent fundamental work in the field of product diffusion. These models have the crucial disadvantage that they are based on a fixed mathematical form. Various authors have tried to compensate for these disadvantages by modifying individual models, by combining different models or by creating completely new models. For an overview, see e.g. [22]. For this paper, these models were not considered.

For the prototypical application, the Bass model was chosen. This is because there are a number of publications that model comparable technologies with its help (listed in table 2).

The values determined with the help of these methods are of course already used in production program planning and thus influence capacity dimensioning. However, normally only the static data determined once is used. For the factory planner, this results in a rigid numerical framework, although changes in market adoption can occur very quickly, especially with new technologies. By integrating diffusion models into the planning process, more differentiated statements can be made, especially with regard to strategies for capacity flexibilization, since this makes it possible to include different adoption processes during planning.

The following section describes the integration of the bass diffusion model in the capacity planning for an assembly line of fuel cell stacks.

4. Application in the assembly of fuel cell stacks

Although the fuel cell was invented as early as 1839 by William Grove [28] and has since been tested many times in various fields of application, its use for a broad market has only recently been pushed. The driving force behind this development can be identified primarily in a growing social awareness of the environment, which is leading to an increasingly critical questioning of conventional drive technologies. At the same time, today's technologies and findings enhance the performance of the fuel cell and can limit application-related dangers and disadvantages. For these reasons, many indicators argue for a disruptive innovation character [29], which exhibits promising future potential in mobile, portable and stationary applications.

At the same time, the technology has disadvantages that could impair rapid diffusion from today's perspective. On the one hand, the production of fuel cell drives is very cost-intensive compared to other drive concepts. Cost drivers are the raw materials needed to manufacture the multi-electron unit [30], the pressure-resistant tank system [31] and the environmentally friendly production of the hydrogen [32]. On the other hand, historical market data show that gaseous fuels tend to be avoided because of the hazards associated with them [33]. Factors such as these endanger adoption in the passenger car market. However, the implications of these factors are much less significant for the operation of fuel cells in trucks or buses. According to a study, which was commissioned by the German state of Baden-Württemberg, this market is growing faster than the passenger car market [34]. Based on the study, two scenarios were defined, which show the course of demand for a pessimistic and optimistic development. Since the characteristics of these scenarios are relatively static and innovation-typical influences are largely neglected, the values were inserted into the model equation according to BASS to determine the model parameters for innovation (p), imitation (q) and potential market size (m). A geometric average was taken over all ten generated value triplets. As a result, the following values can be determined:

Table 1: Diffusion parameters derived through regression analysis

Scenario	p	q	m
Minimum	0,016164	0,522596	100.000
Maximum	0,025612	0,547746	250.000

As the plausibility of the values can only be derived from the numerical amount to a limited extent, publications with similar applications were used as a basis for comparison. Table 2 gives an overview of the authors with the corresponding reference product. Although there is a high degree of scattering among the publications, it can be stated that the values determined fit the model applications typical for the industry.

Table 2: Diffusion parameters for similar products

Authors	Product	p	q	m
Lukas et al. [35]	Electric vehicle batteries	0,022	0,413	2.150.00
Massiani & Gosh [36]	LPG-vehicles in Germany	0,0779	0,3718	75,566
McManus & Senter [37]	Plug-in hybrid electric vehicle	0,00262	0,70935	1.922.806
Li, Chen & Zhang [38]	BEVs in China	0,0013	0,0839	5.000.000
Becker et al. [39]	BEVs	0,025	0,4	2 scenarios

Using the determined model variables, sales figures can be forecasted according to the expected diffusion course and included in the production program. In this specific example, the production program will focus in particular on the manufacturing of the fuel cell stack (FCS). As one of the main components of the fuel cell drive, an FCS represents a combination of single fuel cells and is therefore composed of a defined number of membrane electrode assemblies (MEA), bi-polar plates, seals and end plates [40]. The various components are pressed together in a multi-stage process and then subjected to a leakage test [41]. As an example, the stacking system will now be used to show how the change of diffusion parameters influences the capacity of the production system to be planned. Assuming a 2-shift system and a process time of 30 min per FCS, this can be determined by the number of systems required (Figure 2).

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Year
p	0,016164	0,025612	0,038418 (+50%)	0,025612	0,025612	
q	0,522596	0,547746	0,547746	0,821619 (+50%)	0,547746	
m	100.000	250.000	250.000	250.000	375.000 (+50%)	
Number of Stacking Systems	1	1	1	1	1	1
	1	1	1	1	1	2
	1	1	2	2	2	3
	1	2	3	3	3	4
	1	3	4	4	4	5
	1	4	5	6	6	6
	2	5	6	7	7	7
	2	6	7	8	9	8
	3	7	8	8	10	9
	3	8	8	8	11	10

Progression Curve

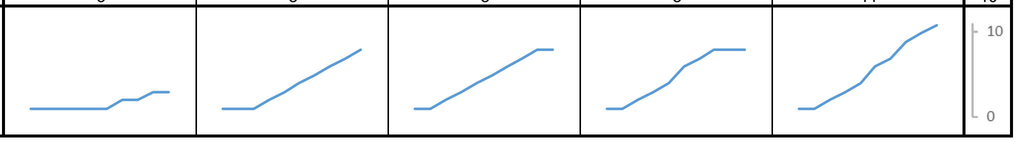


Figure 2: Correlation between diffusion parameters and needed capacity of FCS stacking systems

5. Discussion

Figure 2 shows five different scenarios with their parameters (p, q, and m), the number of required stacking systems and the progression curve for a better visualization of the development of the required capacity. Scenario 1 corresponds with the minimum scenario in table 1. In the first ten years, the required capacity is slowly increasing only in the seventh year an additional system is required. In this scenario, it is not advisable to invest in a second system from the beginning. Especially considering that the price for one system is about 700.000 € [42] leading to high and unnecessary capital commitment costs. Scenario 2 is in line with the maximum scenario from table 1. Here, compared to scenario one, a significantly faster increase in the number of systems required can be seen, with one system still being sufficient in the first three years. Scenarios 3 to 5 show different variations of scenario 2. The parameters of p, q and m are successively increased by 50%. The change of the innovation parameter p leads to the smallest impact on capacity dimensioning. Increasing parameter q in scenario 4 results in a similar outcome compared to scenario 3. Scenario 5 shows the fastest increase in required systems, showing that the market size is the most important factor. Therefore, special attention should be paid here to the determination of this parameter.

The advantage of the presented method compared to conventional capacity dimensioning is that by varying the parameters, more differentiated statements on the capacity requirements of operating resources become possible. This represents a considerable improvement over statements based only on static sales forecasts. The method is a relatively simple procedure that can be applied in small and medium-sized companies. Typically, such companies do not have a large market research department, which means that they rely on freely available or paid studies when planning the sales of innovative products. With the help of the presented method, the data from these studies can be processed and used to compare different possible diffusion patterns and thus capacity curves.

Despite the fact that the capacity dimensioning has been made more flexible by the method presented above, the consideration is still very static. The influence of other variables, such as politically desired expansion targets for fuel cell fleets, can or even must be considered. Despite the relative simplicity, expert knowledge is rather necessary compared to the use of ready-made studies, which leads to a greater effort. More complex statements and progressions can only be achieved by using other diffusion models. However, these require a more in-depth knowledge of diffusion research methods.

6. Conclusion

The importance of alternative drive technologies is increasing. Currently battery-electric vehicles are in the spotlight of companies, research and buyers. Fuel cell technology is another contender to make mobility more sustainable. Companies that want to invest in this market are faced with the challenge of assessing how the market will develop. Market developments also determine how much production capacity is needed. Working with static figures alone for dimensioning can lead to misjudgements and thus to malinvestments. To avoid this, a general method was presented in the paper that integrates insights from innovation management into factory planning. For that purpose, the paper presented the traditional approach for capacity dimensioning in factory planning projects. A short overview was given on the subject of innovation diffusion models, as a group of models suitable for forecasting future demand of innovative technologies. Various scenarios were set up using the Bass Diffusion model to size the demand for stacking systems in the assembly of fuel cell stacks. The values for this were determined using a regression analysis from a public study. The plausibility of the regression analysis was checked by comparing the values with those of other similar technologies. The method results in different curves for the need for stacking systems over time. Based on the curves, factory planners can make a better estimate of the flexibility strategy to be selected.

Future research and application of this method should concentrate on following aspects. Currently, only variations of the parameters of the Bass diffusion model are considered. They can be seen as a summary of different factors and influences, but a further differentiation of the influencing factors can be made. For further modelling, a system dynamics approach can be used to investigate the influencing factors, which may also result from legal and political conditions. Currently, the described method exists only as an application in Excel. However, in order to enable the dissemination in practice and to improve the usability, it is advantageous to implement the method in existing software solutions. The extent to which the method can be integrated into already established factory planning processes requires further investigation. For this purpose, the use in a real application scenario is desirable.

Acknowledgements

The authors gratefully acknowledge the financial support of the Kopernikus-project "SynErgie" by the Federal Ministry of Education and Research (BMBF) and the project supervision by the project management organization Projektträger Jülich (PtJ).

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Biography

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Marian Süße (*1992) started working at the Fraunhofer-Institute for Machine Tools and Forming Technology IWU as a Student Assistant in 2014. Since 2017 he is working as Research Associate in the Department Factory of the Future where he is in charge of the Group for Factory Design and Simulation since 2018. In his research and PhD-Thesis, he focusses on the development of methods for factory layout planning and layout optimization approaches as well as ecologic impacts of production systems.

Steffen Ihlenfeldt (*1971) studied at the TU Braunschweig and has been a member of the Fraunhofer Institute for Machine Tools and Forming Technology IWU in various positions since 1997 at. He received his Doctorate in 2012. Since 2015 Prof. Dr.-Ing. Steffen Ihlenfeldt has been called to the Position of Professorship for Machine Tool Development and Adaptive Control systems at the TU Dresden. In addition to his work at the TU Dresden, he is Institute Director of the Fraunhofer IWU, responsible for the scientific field of Production Systems and Factory Automation.