Scenarios for Solar Thermal Collector in Germany

Master Thesis

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Abstract

Climate change has set on the spotlight micro-generation technologies; however, solar thermal systems, an example of renewable energy sources, are facing difficulties in standing out from other renewable heating sources.

In Germany, for instance, the primary residential use of energy is space heating and warm water. Solar thermal systems can cover almost 100% of these needs during the summer season, by converting the sun heat directly into warm water. Moreover, in 2015 financial-aid has been reintroduced by the Federal Office for Economic Affairs and Export Controls (BAFA) and the German state-owned development bank (KfW) to promote the acceptance of the solar thermal systems. Notwithstanding, the Solar Thermal Systems in Germany have been losing market to other green alternatives.

Thus, regardless of being environmentally friendly and having incentive programs in place, in Germany, the Solar Thermal Systems market is believed to have entered the declining phase. One of the suspected causes of such a phenomenon is that consumers prefer a technology that generates not only heat but also electricity and gives access to the feed-in tariff. Also, installers, as the recommendation source, rather suggest other technologies easier to install and easier to sell, meaning low cost.

Therefore, the combination of the already mentioned socio-economic factors might be causing the decline of solar thermal in Germany. What's more, it creates uncertainty for the companies offering this technology, as it is not clear what forces are driving the diffusion of solar thermal, which perhaps causes managers inaccuracy in their predictions.

That being said, this research will attempt to reduce, at a macro-level, the uncertainty of Solar Thermal Collectors market acceptance, in Germany, by applying the scenario planning theory – built on Intuitive Logics –by Derbyshire and Giovanetti (2017) to the business case provided by Company X. The objectives of this thesis are to (1) identifying the two most critical socio-economic driving forces and (2) developing four plausible scenarios for 2021. To achieve these objectives quantitative techniques such as seasonal forecasting technique, based on least squares, multivariate regression analysis, and the Bass growth model have been used. Also, qualitative techniques such as the conceptualization stage of system dynamics and the critical scenario method are used in the methodology of this research.

This master thesis concludes, from the analysis conducted, that the solar thermal collectors' German market will keep its negative trend by 2021, if everything remains the same. Also, the two critical forces which slow the adoption of solar thermal collectors in Germany are the awareness/knowledge of the end-consumer towards the technology (consumer interest) and the final price (cost) of the technology. On the other hand, subsidies, as expected, don't have an influence on the adoption of solar thermal collectors. As a result, the following four scenarios were framed: market growth, market uncertainty, market revitalization not materializing and market stagnation.

Finally, this study recommends conducting a future end-consumer tailored research to investigate the households' level of awareness about solar thermal collectors and their likelihood of adopting the technology in the near future.

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1 Introduction

According to the literature environmental factors such as market, technology and policy developments, as well as social-network factors and stakeholder motivations, not only drive the diffusion of a product but also makes it uncertain (Vecchiato and Roveda, 2010). Uncertainty refers to the inability to make accurate predictions. Hence, environmental uncertainty arises when managers lack confidence in predicting what the significant changes are or will be regarding the business micro and macro environment (Vecchiato, 2012).

Understanding and identifying the source of uncertainty and its possible effects can assist decision-makers in defining courses of action and, ultimately, superior firm performance (Rohrbeck and Kum, 2015). Scenario Planning is a framework - strategy formulation oriented - which has been increasingly viewed as a tool for assisting the visualization of alternative futures. It empowers practitioners to consider complex management issues in a storytelling way (Laurent et al., 2015). Scenario planning acknowledges uncertainty by considering factors such as legal, politics, technology and societal (Wright et al., 2013), as exemplified by Wack (1985) in his article Scenarios: Uncharted Waters Ahead. There is ample research about this methodology; different frameworks have been introduced. For instance, Fink and Schlake (2000) proposed a five-phase process to develop scenarios, which the main components are systems thinking, strategic thinking, and future-open thinking. Kayser and Shala (2016) introduced a process with only three steps, which they optimized through text mining. More recently, Derbyshire and Giovannetti (2017), proposed an augmented version of scenario planning for NPD, built on intuitive logics, - better known as the Shell approach. The framework by Derbyshire and Giovannetti (2017) aims to mitigate uncertainty, more precisely, about new product market-acceptance by identifying drivers of change and critical forces, understanding their cause-effect in the system, as well as their level of impact and uncertainty, and finally developing future scenarios. Laurent et al. (2015) classified drivers of change as all sorts of events that influence the phenomenon under study; and critical forces, as the main drivers that cause the most impact and are highly uncertain. Moreover, augmented-NPD IL approach, by Derbyshire and Giovannetti (2017), combines qualitative aspects of social-economic factors with quantitative extrapolation forecasting techniques.

Identifying the drivers of change and their interactions and envisioning plausible futures is essential for complex - dynamic - systems, such as companies in the market of solar thermal systems. Although climate change has set the spotlight on micro-generation technologies, solar thermal systems are facing difficulties in standing out from other renewable heating sources (EurObserv'ER, 2018). For instance, Company X, a company headquartered in the Netherlands with international participation in the smart climate heating solutions, recognizes this current phenomenon of solar thermal collectors losing market to other (electric) heating alternatives. Although the primary use of energy in Germany is for heating and hot water, the German market of solar thermal systems and the company's product sales volumes have been declining gradually since 2011. Thus, developing augmented NPD intuitive logics scenarios for this market, in collaboration with Company X, sounds suitable to cope with the uncertainty of the product by understanding what drives the market, and unfold the possible futures for this technology - whether the market will change its current pattern or not.

Laurent et al. (2015) highlighted that scenario planning, based on the intuitive logics method, can be customized to any system of any scale and be applied to different disciplines.

Therefore, the research question of this study is:

Will the adapted version of scenario planning by Derbyshire and Giovannetti (2017), when used in existing products - such as solar thermal collectors - of Germany, mitigate environmental uncertainty?

This study attempts to answer the main research question by the following two sub-questions:
- What are the two main socio-economic forces that drive the solar thermal collector market in Germany?
- What are the four plausible futures of solar thermal collectors in 2021 for Germany?

The answer to these questions will help to achieve the objectives of this study, which is to (1) cope with the uncertainty that the solar thermal market is facing now and (2) foresee under which condition could the solar collector market peak in the near future (2021).

This thesis aims to contribute as empirical evidence to the scenario planning literature by developing the business case of Company X's solar thermal collectors, through the theory of Augmented NPD IL Scenario Planning proposed by Derbyshire and Giovannetti (2017); thus, no new product introductions will be discussed in this research. Moreover, there is a lack in the literature about IL scenario planning on renewable energy sources, specifically on solar thermal collectors. Hopefully, this study helps to fill the gap.

It is expected to achieve satisfactory results; as Laurent et al. (2015) stated it, intuitive logics scenario planning can be customized to any complex system. Regarding the main driving forces impacting the diffusion of the solar thermal collectors in Germany, it is expected that the cost of adopting the technology has a negative impact as Huang et al. (2019) found that in China solar thermal systems cannot compete against electric or gas water heaters without subsidy programs. Different from China, in the Netherlands, according to Jager (2006), grants covering almost 90% of the cost of PV collectors didn't incentive the adoption as expected – this due to the lack of awareness of the product. The legal factor is also expected to have a significant impact on the solar thermal collectors' market, as the EU regulates the renewable energy systems mix that each EU country should have to achieve the EU 2020 strategy.

The study is structured as follows: Section 2 reviews the literature about scenario planning. Section 3 describes the methods to be used. Section 4 presents the results of the application of the adapted version of Derbyshire and Giovannetti (2017) methodology in the business case. Section 5 presents discussion and conclusion. Section

2 Literature Review

2.1 Scenario Planning Theory

Scenario planning is a practitioner strategic planning tool, which aims to improve the decision-making process against a background of possible future environments (Schoemaker, 1992). More specifically, Schoemaker (1991) defined scenarios as "a script-like characterization of a possible future presented in considerable detail, with special emphasis on causal connections, internal consistency, and concreteness." Herman Kahn, who is considered the father of scenario planning, defined it as "a set of hypothetical events, which are set in the future constructed to clarify a possible chain of causal events as well as their decision points" (Amer et al., 2013). Scenario planning can improve managers' decisions by enhancing their mental models about the future, and incorporating to their forecast technology planning, strategic analysis, and future studies. Scenario planning is a set of narratives that emphasize the unexpected and extreme future outcomes of drivers of change, or what Derbyshire and Giovannetti (2017) refer to as crucial decisions. However, scenario planning should not be treated as a forecasting technique, as future forecasting purpose is to identify the most likely pathway, whereas scenario planning explores multiple plausible future outcomes resulting from uncertainty (Amer et al. 2013). According to the experience of Andre Benand, Shell's former group managing director, scenario planning nudges more people to think about the future than forecasting techniques (Wack, 1985).

Not only academics (Kayser and Blind, 2016), but also governmental organizations such as EUISS (2017) recognize scenarios as a framework to support decision-making based on possible future events.

Scenarios are not exclusive for research and policy-making since the 70's companies have been harnessing from scenario planning. The most known example that put scenarios in the spotlight was Shell's response to the oil crisis in 1973. Having been prepared for a plausible scenario helped Shell to become one of the top three players in the oil industry (Vecchiato, 2012).

There are several methodologies to generate scenarios, the most popular ones in literature are those from Schoemaker (1992 and 1995) and Wack (1985), both former employees of Royal Dutch Shell. Schoemaker (1995) described a 10-step process to build scenarios as a shared framework for strategic thinking that encourages diversity and sharper perceptions about external changes and opportunities. On the other hand, Wack (1985) described how scenarios were developed at Royal Dutch Shell, back in 1970, as a sort of a guide. Moreover, scenario planning reviews such as the one from Amer et al. (2013) and Keough and Shanahan (2008), to mention a few, describe different methodologies as part of their literature body.

The use of scenario planning has increased in the last decade, this as a result of the increasing uncertainty and unpredictability of the business environment. Therefore, a large number of techniques and methods have been developed. In general, the scenarios can be classified into descriptive and normative scenarios. Descriptive scenarios are those which in nature are explorative and introduce several future alternative events. Normative scenarios are those for policy planning (Amer et al., 2013). Moreover, scenarios can be classified by field of research, technology, or social, the scope of analysis, macro - microenvironment, and time horizon, short-medium term oriented (Vecchiato and Roveda, 2010).

In general, all scenario planning methodologies are categorized within three major approaches (Amer et al., 2013); intuitive logics, probabilistic modified trends, and La prospective.

The methodology of Intuitive Logics, which was proposed firstly by Herman Kahn, is widely known as the Shell approach, after being used by the company (Amer et al., 2013). It focuses on developing multiple scenarios that explore how the future might evolve from today's point of time to the horizon year of the scenario. Moreover, it analyzes the relationships between critical uncertainties, relevant predetermined trends, and the behavior of actors who have a stake in a particular future. Furthermore, this approach integrates the political, economic, social, technological, ecological, and legal factors, which are thought to be the ones shaping the future. In sum, this approach enables the identification of the driving forces, consideration of plausible outcomes, and understanding of how each of these forces interacts with each other in terms of cause-effect - this is done through an eight-step process (Wright et al., 2013).

Probabilistic Modified Trends incorporate two different techniques, trend impact analysis, and cross-impact analysis (Bradfield et al. 2005). Trend impact analysis, an approach that has been practiced since the '70s. It identifies trends and collects time-series data around the selected topic. Moreover, it lists impacting events and establishes probabilities of the occurrence of these events (Huss and Honton, 1987). Like trend impact analysis, cross-impact analysis identifies key indicators, identify impacting events and develop probabilities of distribution of the events. In short, both techniques involve the probabilistic modification of extrapolated trends (Refer to Bradfield et al. (2005) and Huss and Honton (1987) for more details.)

La prospective approach, introduced by the French philosopher Gaston Berger, looks at the future as independent of the predetermined temporal continuity, and it can be shaped. The main purpose of this method is to understand the contemporary world and the hidden danger. The key difference between the English and French methodologies to develop scenarios is that English scenarios tend to be global, while the French scenarios focus on socio-political matters. Therefore, it is implied that La prospective approach develops normative scenarios. Moreover, Bradfield et al. (2005) summarized La prospective as a combined approach of intuitive logics and probabilistic modified trends.

Derbyshire and Giovannetti (2017) developed a nine-step scenario planning process, built on intuitive logics. Figure 1 describes both frameworks. The application proposed in their research aims to mitigate uncertainty about NPD market acceptance; moreover, they incorporated qualitative social-economic factors dynamics with quantitative techniques, such as forecasting techniques and diffusion models to strengthen the impact of the scenarios presented. The authors suggest that by taking into consideration stakeholders' motivations as well, it can determine better which scenario could unfold. This research provides a step-by-step guide for scenario building for new product development. Although the authors claim that there is no previous research that combines both quantitative and qualitative techniques for scenario planning, La prospective is the scenario planning technique that bridges experience and data (Amer et al., 2013). Moreover, Rohrbeck and Kum (2015) list several companies that have practiced La prospective.

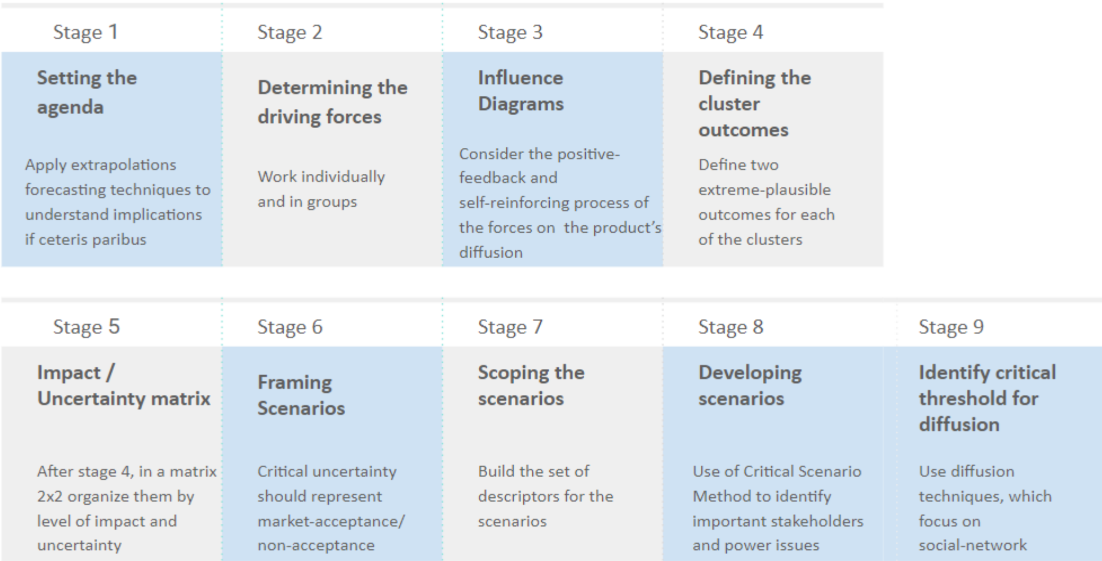


Figure 1: Augmented NPD IL Scenario Planning framework, adapted from Derbyshire and Giovannetti (2016). The text-boxes in blue depict the changed steps from Wright et al. (2013) method.

Thus, applying Derbyshire and Giovannetti (2015) framework in this research can only extend and complement the current literature about scenario planning. Moreover, what hopefully will be of a new contribution is the topic on Solar Thermal Collectors.

2.2 Methods for Augmented IL Approach

Derbyshire and Giovannetti (2017) proposed for their scenario planning method, both simple and advanced forecasting techniques such as seasonal forecasting technique, based on least squares, and the Bass growth model that could be used to mitigate uncertainty NPD-wise. Also, they recommended influence diagrams and critical scenario method - to assess the effects of social-economic forces and the motivations of stakeholders on the (uncertainty) of product growth. The following subsections review these techniques.

Forecasting techniques: Time series

Derbyshire and Giovannetti (2017) argued that a historical perspective should be considered to understand the implications of the (future) success or failure of a product.

Extrapolation forecasting techniques are developed considering the past trajectory, for example, of sales, demand, and production plans. This approach assumes that whatever phenomenon was causing *"sales"* to vary from period to period in the recent past will continue (Asking and Goldberg, 2002).

There are different methods for extrapolation forecasting; for instance, Dalrymple (1987) found that companies used regularly the naive approach; however, the accuracy of this technique is questionable. This technique uses the last period's values as the (next) period's forecast. Naïve model is as follows:

$$\hat{Y}_{t+1} = Y_t$$

Least squares, a technique for multiple regression analysis, is another way of forecasting. As it is a relatively simple approach. The information required to perform a forecast, for example, is the historical sales or demand of a product - as the dependent variable, the coefficient of the intercept of the model, as well as the ones from the independent variables - which could be the quarter, months, years - and the predicted values. Ideally, it is expected to forecast the exact future's values; however, in dynamic environments, forecasts have limited accuracy, meaning that the estimates forecasted will usually contain some errors. Nevertheless, least-squares forecasting modeling can improve its accuracy by combining seasonal indices with other explanatory variables (Landram, 2011). The later mentioned only applies to time series data. The following table describes the components needed to perform a forecast based on least squares and seasonality index:

Period	1, 2, 3, …, n
Predicted Variable	Integer
Least Squares: **Linear Trend** **Seasonal Component**	y = a + bx(i) where *a* is the intercept, *b* is slope, and *i* is seasonality index $a = \bar{\bar{y}} - b\bar{x}$ $b = r(\frac{S_y}{S_x})$ $i = (\frac{\overline{d_{s,t}}}{\bar{d}})$
Upper and Low Bound	$\breve{y} \mp 2 * \sigma/\sqrt{n}$

Table 1: Components for predictions based on least squares and seasonality index

Furthermore, multiple regression can also describe the relationship between a single dependent variable and several independent variables; both variables should be metric. The objective is to use several independent variables to predict the single value of the dependent variable. A typical application of this technique is a company interested in predicting the satisfaction level of its customer (DV) based on the perceptions of the company's performance, for example, product quality (IV), advertising (IV), delivery speed (IV). The model which explains the relationship between variables is the same as the one previously mentioned for forecasting. The regression model is as follows:

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_t x_t + \varepsilon$$

where $\hat{Y}$ is the variable to be predicted (sales volume DV), x_t are the observations used to predict $\hat{Y}$, β_0 is the intercept, β_t represents the slope coefficient from each of the independent variables, and ε stands for the regression residual (the error). This model applies only to cross-sectional data.

When the dependent variable and/or the independent variables of the model are observed overtime at monthly or quarterly intervals, the data might exhibit a time trend and/or seasonality. According to the textbook, Introductory Econometrics by Jeff Wooldridge, the simplest way to account for the time trend and seasonality is to include in the regression model, a time trend variable (1,2,3… n) and seasonal dummy variables (0,1). The equation for a time series regression model is as follows:

$$\hat{Y} = \beta_0 + \delta_1 jan_t + \cdots + \delta_{11} nov_t + \beta_n t + \varepsilon$$

where jan_t, …, nov_t are the seasonal dummy variables (assuming December as the month base) and $\beta_n t$ is the time trend.

Including time trend and seasonal dummy variables in the regression model prevents the possibility of finding a spurious relationship between the explained and the explanatory variables (Landram, 2011).

Network externalities

Valente (1996) defined diffusion of innovation as the process of the initial adoption of innovation within a social system, which over time will be adopted by more members until the complete social system acquires the innovation. Diffusion of innovation is also known as the bandwagon effect, or network effect, which is supposed to trigger market growth; because it is assumed that consumers derive utility from a technology based on the number of other users. However, this same effect could neglect diffusion of innovation as well, as users will "wait-and-see" the utility derived from the few adopters (Goldenberg et al., 2010). Thus, exploring the network externalities (direct and indirect), which influence the diffusion of innovation and hence the market growth or contraction, will help to cope with effect uncertainty.

Two approaches, to mention a few, that can assist with the diffusion of innovation, and the uncertainty effect, are the Bass model (Scaglione et al., 2015) and the Threshold model (Valente, 1996). Both models are based on network externalities; however, threshold model is mostly used to understand the influence of externalities on the diffusion of innovation, while the Bass model is used to forecast the adoption of innovation (product). Fortunately, both models can be combined as Scaglione et al. (2015) did. They forecasted the diffusion of mobile social networking by taking into consideration the influence of (direct) externalities. Another example of the Bass Model is the study conducted by Islam (2014), who hypothesized that the diffusion of solar photovoltaic systems is driven by endogenous factors, awareness, and knowledge of the technology; and exogenous factors, cost, regulations and market structure. After conducting a discrete choice experiment, the adoption probabilities were calculated to predict the innovation diffusion of PV – an extended version of the Bass model was used. He concluded that households who have higher awareness levels and are less sensitive to cost-related factors are more likely to adopt early PV technology.

The Bass growth model (1969) suggests that product diffusion depends on two coefficients: innovation (p), that is, consumers who adopt the product early, and imitation (q), meaning that consumers adopt a product because others have done it before. Meaning that the timing of a consumer's first purchase is related to the number of previous buyers. Also, the model assumes that the product is purchased only a single time. In fact, the Bass (1969) growth model is one of the first attempts – back in the '50s and '60s – to answer whether the life cycle of a new product could be predicted (Nair, 2019, p.361). More precisely, the Bass (1969) model was developed with the goal of reflecting and forecasting the growth pattern of a product's life cycle, that is, sales grow to a peak and then drift downward at some point lower than the peak. Moreover, Bass (1969) incorporated to his model Roger's (1962) adopter categorization, based on the time of adoption, this with the idea of showing the behavioral rationale of the model. Figure 2 shows the relation of the product life cycle, the Bass diffusion model curve and the classes of adopters.

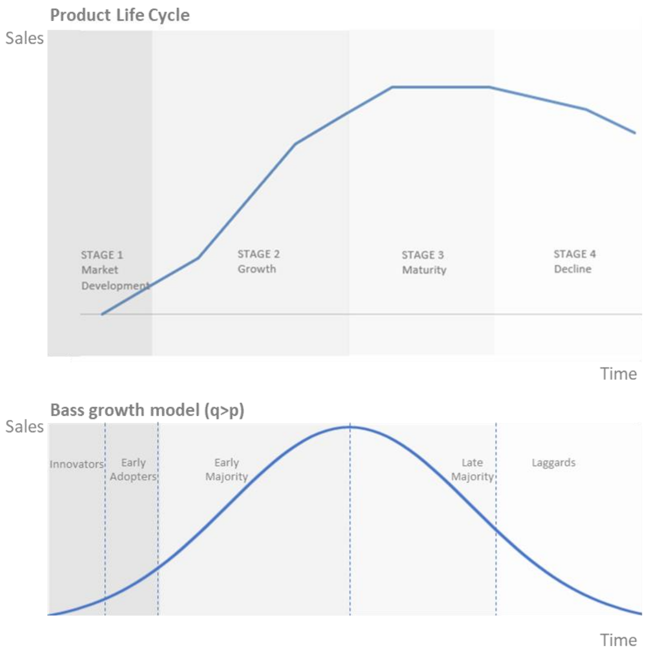


Figure 2: Product Life Cycle curve adapted from Levitt (1965), Bass growth model and classes of adopters adapted from Bass (1969) and Rogers (1962).

The basic model suggested by Bass (1969) is:

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

, where $\frac{f(t)}{1-F(t)}$ is defined as the rate of the purchase at time *t*, given no previous purchase, and *F(t)* is the cumulative probability of purchase at time zero by a single person. Solving the differential equation, the following is obtained:

$$F(t) = \frac{p(e^{(p+q)t} - 1)}{p(e^{(p+q)t} + q)}$$

If the parameters p and q are unknown, historical sales and cumulative sales of the product should be substituted in the basic Bass model and finally conduct a non-linear regression. Sales in any period are $s(t) = mf(t)$ and cumulative sales are $S(t) = mF(t)$. The rewrote equation is:

$$s(t) = \left[p + q\frac{S(t)}{m}\right][m - S(t)$$

And therefore,

$$s(t) = \beta_0 + \beta_1 S(t) + \beta_2 S(t)^2$$

where β_0 is pm, β_1 is $q - p$, and β_2 is $-q/m$.

Finally, the Bass growth model is suitable for analysis, which doesn't include variables such as prices and advertising investments. Also, this forecasting model is a good match for analysis at industry-level or category-level (Nair, 2019, p.361)

Agent-based modeling, different from the Bass model, is an individual-level approach, which can be used to examine how network effects drive market growth, including, for example, marketing variables and consumer expectations (Nair, 2019, p.36). Goldenberg et al. (2010) studied the fundamental effects of network externalities on new product growth rates by stimulating the growth of a market for a given product. Through this bottom-up approach, they understand how individual-level network of a product aggregates to market phenomena. More specifically, they show how potential customers may wait for early adopters, who provide them with more utility before they adopt. One of the challenges of applying agent-based modeling, according to Goldenberg et al. (2010), is tying the simulation to empirical data. Although agent-based modeling seems suitable for this research, as it is a good approach for studying human behavior in complex settings, an individual-level analysis of this research is beyond the scope of this thesis.

Influence Diagrams

System dynamics, initiated by Jay Forrester in the ’50s, is a modeling technique that has been used to understand and represent a part of the reality - a social system- based on simulations (Forrester, 1994). Pejic-Bach and Ceric (2007) defined system dynamics as “a powerful tool that enhances learning about the company, market, and competitors, which supports the building of "What if" scenarios. Moreover, Duggan (2006) and Sterman (2000) define system dynamics as a model building process that should focus on scenarios in which decision-makers are facing high complexity, seeking to understand and test the impact of each element of the system.

The building blocks of system dynamics are stock and flows, and influence diagrams - also known as feedback. After combining these elements, models of reality are reproduced. These models can be solved using calculus and the principles of integration (Duggan, 2006). Stocks and flows are the first elements of any system. Stocks are accumulations, and flows are the quantities added (inflow) or subtracted (outflow) from a stock over time (Albin, 1997 and Duggan, 2006). Feedback, or influence diagrams, is a chain of circular causal links, which can be either positive (reinforcing loop) or negative (balancing loop). Feedback loops are a sort of adjustment to the flows, and therefore to the stocks. Duggman (2006), in his book System Dynamics Modeling in R, illustrates several examples of stock, flows, and feedback loops. Sterman (2000) also describes extensively this topic. Albin (1997) wrote under the supervision of JW Forrester a series of papers that describe the process of system dynamic building. The first paper describes the four steps to model-building: conceptualization, formulation, testing, and implementation. The goal of the conceptualization phase is to depict feedback loops diagrams, meaning influence diagrams. Albin (1997) defined the process of conceptualization with a general description of each step. The steps are the purpose of the model, focusing on a problem; the model boundary, meaning defining the endogenous and exogenous components; reference mode, graphs of the evolution of key variables of a system over time; and finally influence diagrams, mapping the mechanism.

Schmidt-Costa et al. (2019) developed, for a deeper understanding, a feedback loop diagram of the photovoltaic collector's diffusion process. Iannone et al. (2015) developed several influence diagrams to understand the cause and effect relationship of the variables within the fashion retail supply chain system. Derbyshire and Giovanetti (2017) suggested influence diagrams as a tool to represent how elements of a scenario planning can affect each other, resulting in a particular outcome - especially in the process of market acceptance.

Critical Scenario Method

Cairns et al (2010) developed the critical scenario method with the motivation of filling the gap, in the academic world, between companies focusing on profit maximization and social groups.

In their research, they explain briefly how scenario planning is developed, and highlighted that the conventional method doesn't incorporate all the actors involved in a scenario. In the critical scenario method, the analysis of stakeholders is at the center of the analysis. Cairns et al. (2010) illustrated that in a matrix of two axis, actors involved and scenarios, each combination should consider two issues - the impact and the likely reaction. This qualitative technique seeks to create awareness of the degree of power of social actors and the impact they might have in, for instance, the acceptance of a product in the market.

3 Data and Methodology

Data

The qualitative information was collected from the BRG Germany market report 2018, and IEA-SHC Germany country report 2019. The BRG report was provided by the product manager of BDR Thermea, the company in collaboration. The IEA SHC market report was obtained through the website of the International Energy Agency, which is considered by the company as a reliable source. Moreover, one of the aims of this agency is to improve transparency among international markets by collecting and providing analysis of energy data. On the other hand, the quantitative data was provided by the product managers of Company X.

Methodology

This study follows the steps proposed by Derbyshire and Giovannetti (2016) to build scenario planning (See Figure 1). First, each step is described; followed by the technique and the data to be used to develop the steps.

STAGE 1 - Setting the scenario agenda

The first step is to make future projections to understand the implications for future demand conditions. The future projections can be done through simple projection-base forecasting techniques and descriptive analysis, such as the current market share.

Therefore, to demonstrate the sales evolution, since their launch day, graphs with the historical market sales will be depicted[1]. Also, to foresee what will the near future look like for the sales volume, if ceteris paribus, a seasonal forecast will be performed based on least squares. Chu and Zhang (2003) stated that this extrapolation forecasting technique is appropriated when seasonal variations are relatively constant.

Moreover, to describe the current situation, a set of relevant chronological events will be mentioned.

[1] Source: Company X

STAGE 2 AND 3 - After identifying and clustering driving forces, influence diagram

In the IL method, the main factors are identified in brainstorming workshops. Participants are asked to list the main drivers of change impacting the object under study (Laurent et al., 2015). However, in this study, the main drivers of change have been identified in the BRG and IEA market reports.

After identifying the drivers of change, the influence diagram is depicted to visualize how the (previously identified) drivers interrelate with each other in the system under study.

The influence diagram will be depicted by (1) considering the causal loop diagram of the photovoltaic systems diffusion process built by Schmidt-Costa et al. (2019), which aims to visualize how network externalities influence the diffusion process of the technology, and (2) following Albin and Forrester's (1997) guide to developing the conceptualization of system dynamics.

As a remark, photovoltaic and solar thermal systems are two types of solar energy. Therefore, because of the lack of research on solar thermal, the model by Schmidt-Costa et al. (2019) is used.

In order to validate the identified drivers of change, additional literature was reviewed about forces that influence the diffusion of solar thermal collectors and solar photovoltaic collectors. Ayadi and Dahidi (2019), in a comparative study of solar energy systems, stated that the slow spread worldwide of solar thermal systems is due to the lack of awareness, technical knowledge, and economic competitiveness. Huang et al. (2019) recognize that in China, solar thermal systems cannot compete because of the new initiatives to support other heating alternatives, such as heat pumps. For instance, residents who install heat pumps or electric boilers have access to subsidies for the adoption of those technologies and subsidies for electric bills. In the Netherlands, according to Jager (2006), grants covering almost 90% of the cost of PV collectors didn't incentive the adoption as expected – this due to the lack of knowledge and information about the technology. Islam (2014) found that in the Canadian market, technology awareness of photovoltaic systems and energy cost savings have a significant impact on the adoption of technology. These forces are summarized in the following table:

Forces	***Solar energy type***	***Country***	***Source***
Lack of awareness, technical knowledge, and economic competitiveness	Solar Thermal	Worldwide	Ayadi and Dahidi (2019)
Subsidies for acquiring other electric heating alternatives and electric bills, for example heat pumps	Solar Thermal	China	Huang et al. (2019)
Lack of knowledge and information about the technology inhibits final users to apply for subsidies - even if they are in place	Photovoltaic	The Netherlands	Jager (2006)

Technology awareness and energy cost savings	Photovoltaic	Canada	Islam (2014)

Table 2: Summary of drivers of change for solar energy technologies found in literature review

STAGE 4 - 6 Extreme outcomes - impact/uncertainty matrix and scenario framing

After the influence diagram is ready, a regression analysis will be conducted to show the influence of the factors in the diffusion of the product. This technique not only reveals the impact of the on the product diffusion, but also the magnitude of it. Thus, the two most influential factors will be picked to continue with the methodology. Saviano and Lourenco (2018) recognize the support of multiple regression analysis in verifying the influence of the predictors in the dependent variable.

After identifying the two most uncertain and with the most impact factors, meaning the critical forces, two extreme outcomes, yet highly plausible, should be defined for each of the factors. In standard IL, a 2x2 matrix is commonly used to represent uncertainty and impact. For the approach proposed by Derbyshire and Giovannetti (2017), uncertainty should be labeled as market acceptance and non-market acceptance.

In this study, the legends in the uncertainty axis will be product growth/product stagnation or product diffusion/product non-diffusion. It might be useful to get feedback from experts on the market to validate the results - at this stage.

STAGE 7 AND 8 - Scoping and developing scenarios

The main goal in these steps is to finally develop stories based on the previous steps, incorporating important stakeholders - using the critical scenario method (Cairns et al., 2010) - and other descriptors such as key events, both known and speculations. The scenarios/ stories should explain the relation cause-effect between events that trigger “expected outcomes” at the time horizon suggested.

STAGE 9 - Identifying critical thresholds

Diffusion modeling techniques, which focus on social-network, cultural, and contagion effects, are incorporated in the approach of Derbyshire and Giovannetti (2017). The use of these techniques is with the idea of identifying critical thresholds points at which the (new) product diffusion will be self-reinforcing. The selected technique should be based on the factors previously identified in stage 6; thus, the reasoning behind of product diffusion, and how stakeholders’ motivations in stage 8 can produce a chill effect in the product’s diffusion.

The Bass Model will be used under the method of non-linear squares (or regression), which was proposed by Srinivasan and Mason (1986), to calculate the parameters of innovation and adoption, and inflex point, which reveals when the innovation (solar thermal collector) will be self-reinforcing - if at all.

To carry out this analysis, the thermal collectors’ sales time series, in units, from 2010 to 2018 of Germany will be used - as it is a common practice in the existing literature (Fan et al., 2017).

Business Case

Before 2015, the solar thermal market in the European Union has been declining. Last 2017, the market contracted by 24.7%. Meaning that this micro-generation technology is struggling to survive in the hot water and heating the European market. Company X, which is a global manufacturer of smart climate solutions, can relate to the last statement. Although the company has identified decreasing trends in the demand of the markets, they have presence, some others depicted a recent growth in demand. Thus, this phenomenon makes this business case relevant to be analyzed, since uncertainty about the future of this product category is raising within the company.

4 Results

Stage 1: Setting the Agenda – Extrapolation forecasting technique

Monthly sales volume data, from Germany 2010 -2018, was used to depict the sales volume trend through time and predict the forecasts for the years 2019, 2020 and 2021.
To predict the values for 2019 -2021 first, the components of linear regression were estimated, the intercept and the slope; and finally, the seasonal index. The following tables describe the variables and show the results:

Period	*1, 2, 3, …, n*
Sales Volume (sqm)	*Integer in thousands*
Intercept	*87,961*
Slope	*-474*
Seasonal Index	*0,52 – 0,58 – 1,09 - … - 0,93 – 0,54*
Upper and Low Bound	∓ 2 * *2,418.92*

Table 3: Components values for forecasting based on least squares and seasonality index

Annual Overview

	Year	Sales	Forecast	Lower Limit	Upper Limit
ACTUAL	2010	932.301			
	2011	1.032.567			
	2012	936.321			
	2013	832.968			
	2014	726.698			
	2015	659.034			
	2016	608.524			
	2017	511.649			
	2018	470.766			
FORECAST	2019				
	2020				
	2021		267.081	262.243	271.919

Table 4: Prediction results for solar thermal collectors in Germany 2021

As a result, the following graph:

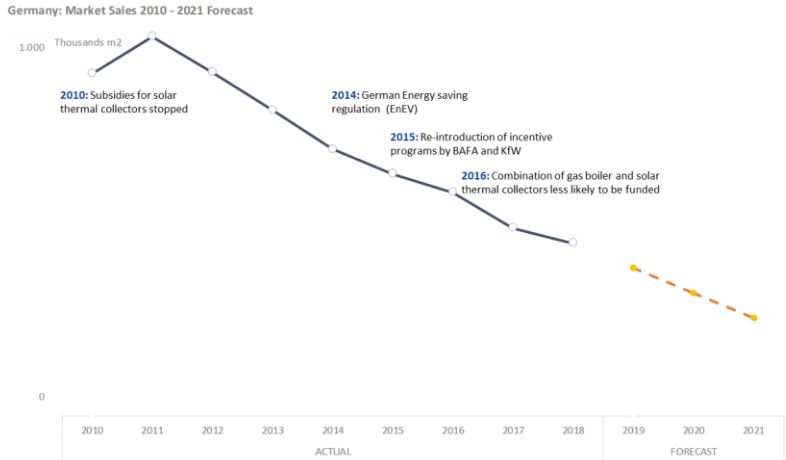


Figure 3| Source: Market sales given by the finance department of Company X. Historical events are taken from BRG May 2019 report. Forecast sales are based on the actual sales (2010 – 2018), considering trend and seasonality index.

Figure 2 describes the sales volume of solar thermal collectors in Germany over time. As shown, the trend for sales is negative. Moreover, the predicted forecast for sales volume 2019 – 2020 (in orange), if ceteris paribus, remains decreasing. Even though incentive programs were re-introduced in 2015, it seems that they don't influence the solar thermal demand (BRG Building Solutions, 2019, The European Heating Product Markets, pg. 163).

Stage 2: Determining driving forces

The driving forces were selected from the BRG Germany Solar Thermal market report 2019, as well as IEA – SHC country report. The driving forces were identified by systematic reading. After, they were classified by the PESTEL analysis. The following are the identified driving forces:

Social:	Opportunity in boiler replacement (first-time installation) Consumer rather invest in a technology that generates electricity and income than just heat and warm water Consumers prefer water heater heat pumps than STS Combi tanks, solar storage tank, and heat pump
Legislation:	Incentive programs reintroduced in 2015 by the Federal Office for Economic Affairs and Export Controls (BAFA) and the German state-owned development bank (KfW) New buildings may be equipped with oil or gas boilers if the res or isolation level increases (EnEV, 2014) Combination of gas boiler and solar thermal, since 2016 less likely to be funded
Economic	Energy and electricity price increased in (2011) to promote wind and solar energy Growth of new build in Germany and non-residential construction Flat plate collectors more common, cheaper than vacuum collectors Government grant schemes

Technology	
	Legislative implementations to increase awareness of STS
	Competition with PV, more developed
	Avg. size has grown
	Solar storage, from 800L to 1,000L
	Solar thermal tanks perform better than collectors

Table 5| Source: Driving forces taken from BRG May 2019 report and IEA-SHC Germany Country Report 2019.

Stage 3: Influence Diagrams – Conceptualization process

Considering the driving forces of Stage 2, which are listed under the endogenous components table, and following Albin and Forrester (1997) conceptualization process – keeping in mind Schmidt-Costa et al. (2019) work, the following influence diagram was depicted:

System: Socioeconomic factors – STS Market Acceptance

Purpose: To understand whether Solar Thermal Collectors demand increases if subsidies in Germany are in place, as well as consumer interest for the technology.
Purpose: To understand whether consumer digital interest affects Solar Thermal Collectors demand.

Endogenous components

Social components	Economic Components
Consumer Interest	Subsidies
Financial benefit	Buildings can be equipped with oil or gas
Interest for another technology	Gas boiler and solar thermal less likely to be funded

Table 6: Driving forces of the solar thermal collectors' market in Germany.

Reference Mode:

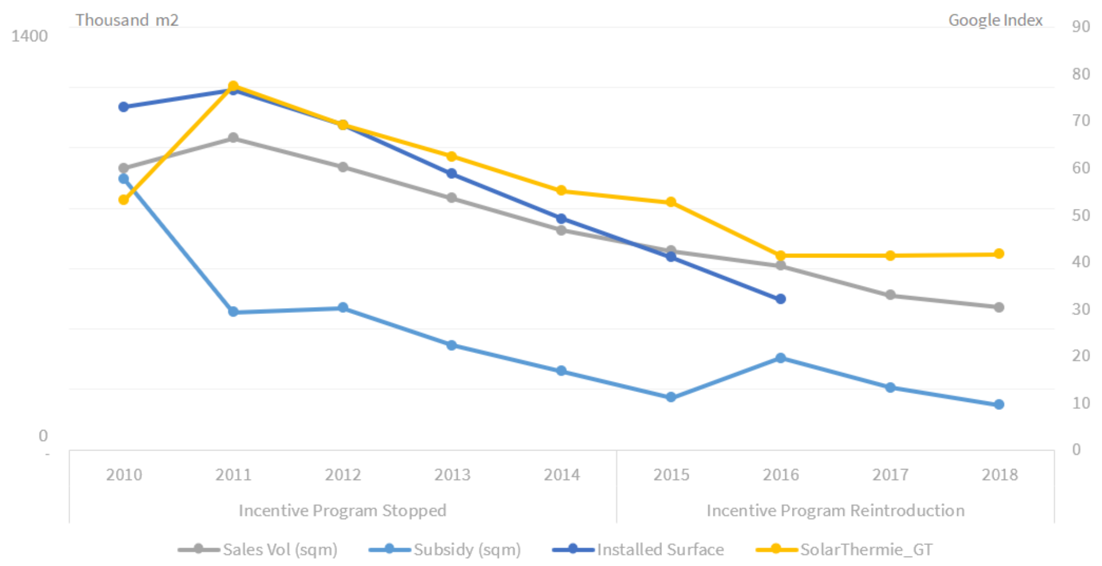


Figure 4 | Germany: 2010 – 2018 Trends of Sales Vol, Subsidy Applications, Installed Surface and Consumer Interest

Influence diagram

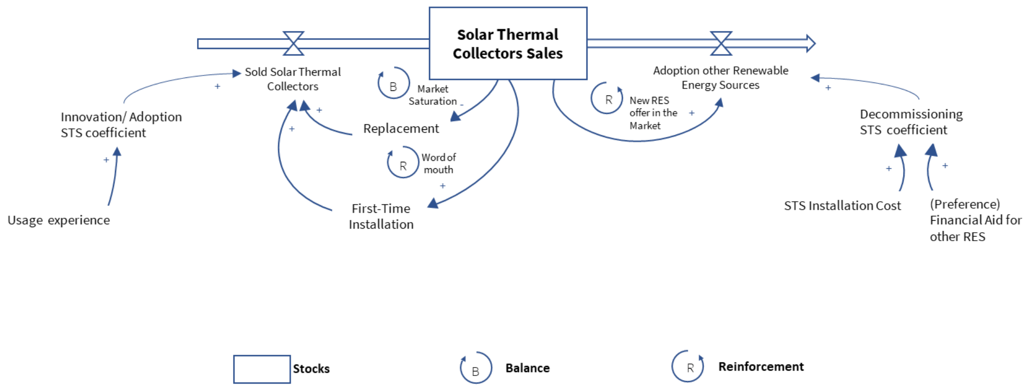


Figure 5 | System: Socioeconomic factors – STS Market Acceptance.
Source: Model adapted from Schmidt-Costa et al. (2019). Driving forces taken from BRG May 2019 report and IEA-SHC Germany Country Report 2019.

Stage 4-6: Impact/Uncertainty matrix

The impact of the driving forces on sales volume for solar thermal collectors can be quantified by translating each/or some of the driving forces into a quantitative measure. Multiple regression analysis can assist in not only predicting but measuring the influence of the factors in the experimental variable.

Considering the found drivers of change in literature and in the market reports, the following model aims to measure the influence of the environmental forces on the diffusion of solar thermal collectors.

$$\mathrm{Ln}(salesvol) = \beta_0 + \beta_1 \mathrm{Ln}(subsidies) + \beta_2 consumerinterest + \beta_3 reintrosub + \varepsilon$$

Germany sales volume in sqm (*Ln(salesvol)*) is determined to be the dependent variable, this is considered as a proxy measure of the diffusion of solar thermal collectors – under the premise that solar thermal collectors are infrequently purchased, and therefore the unit's sales product will coincide with the number of initial purchases, excluding replacements (Bass, 1969). Also, it has been found in research that sales are the result of marketing efforts such as advertisement and word of mouth (Fan et al., 2017).

From all the previous drivers of change identified, the following independent variables were included in the model because of the availability of data. The first variable is the given subsidies (*(Ln(subsidies)*) in Germany for solar thermal collectors (sqm). Consumer interest is measured under the google index for the term "solarthermie" (*consumer interest*), as Schaer et al. (2019) suggest in their work that the popularity of a search keyword may reflect consumer interest in a product and also the success of advertising efforts. Finally, a dichotomous variable was included to compare the adoption of solar thermal collectors if incentive programs (*reintrosub*) are in place. The monthly data used accounts for the years 2010 to 2018.

After meeting all the assumptions for multiple regression, transforming sales volume and subsidies variables into log variables, two models were estimated. The first one measures the influence of the factors in the dependent variable, and the second one can be used for prediction.

Model 1 | Regression on residuals

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.429[a]	.184	.160	.86339184	1.842

a. Predictors: (Constant), Standardized Residual_Reintro_Sub, Standardized Residual_LnSub, Standardized Residual_SolarThermie

b. Dependent Variable: Standardized Residual_LnSales

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-2.224E-14	.083		.000	1.000	-.165	.165					
	Standardized Residual_LnSub	.084	.089	.084	.938	.350	-.093	.261	.051	.092	.083	.986	1.014
	Standardized Residual_SolarThermie	.425	.093	.425	4.579	.000	.241	.610	.421	.410	.406	.909	1.100
	Standardized Residual_Reintro_Sub	-.006	.093	-.006	-.063	.950	-.190	.178	-.132	-.006	-.006	.911	1.097

a. Dependent Variable: Standardized Residual_LnSales

Table 7 | Variables introduced to multiple regression 1 analysis and their coefficients.

$$\mathrm{Ln}(salesvol) = 0{,}084\mathrm{Ln}(subsidies) + 0{,}425consumerinterest - 0{,}006reintrosub$$

Although the model is statistically significant, it cannot be concluded that the variable of Sales is influenced at all by Subsidies. However, consumer interest, measured by the google search index, has a positive effect on Sales; its coefficient is statically significant. Additionally, consumer interest is the variable which influences the most the dependent variable, as the absolute value of the standardized coefficient beta is 0,425. Moreover, it can be understood by the Adjusted R Square (.160) that there are other factors that affecting Sales, which are not captured in this model.

Because of the results, model 1 is not sufficient to make predictions ($\overline{R_2}$ = 0,160), model 2 was estimated, by only including explanatory variables to model 1 - a trend variable and monthly dummy variables:

$$\mathrm{Ln}(salesvol) = \beta_0 + \beta_1\mathrm{Ln}(subsidies) + \beta_2 consumerinterest + \beta_3 reintrosub + \beta_4 t + \delta_1 jan + \delta_2 feb + \cdots + \delta_9 dec + \varepsilon$$

Model 2 | Including Seasonal Dummy and Time Trend variables

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.942[a]	.888	.869	.15901	1.842

a. Predictors: (Constant), Month_Dec, Sub_Yes, Month_Nov, Month_Oct, Month_Sep, Month_Aug, Month_Jul, Month_Jun, Month_May, Month_Apr, Month_Feb, Ln_Sub, Month_Mar, SolarThermie_GT, Time_Trend

b. Dependent Variable: Ln_Sales

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	9.946	.378		26.336	.000	9.196	10.696					
	Time_Trend	-.005	.001	-.363	-4.610	.000	-.007	-.003	-.533	-.433	-.161	.197	5.082
	Ln_Sub	.028	.032	.045	.882	.380	-.035	.091	.237	.092	.031	.475	2.104
	Sub_Yes	-.004	.065	-.004	-.059	.953	-.132	.124	-.502	-.006	-.002	.228	4.389
	SolarThermie_GT	.007	.002	.249	4.307	.000	.004	.011	.593	.410	.151	.365	2.737
	Month_Feb	.054	.077	.034	.698	.487	-.099	.206	-.332	.073	.024	.519	1.926
	Month_Mar	.665	.079	.420	8.466	.000	.509	.821	.096	.662	.296	.497	2.012
	Month_Apr	.769	.081	.486	9.468	.000	.608	.931	.164	.703	.331	.464	2.154
	Month_May	.751	.079	.474	9.543	.000	.595	.908	.139	.705	.334	.495	2.022
	Month_Jun	.845	.078	.533	10.783	.000	.689	1.000	.191	.747	.377	.500	2.001
	Month_Jul	.798	.075	.504	10.578	.000	.648	.948	.128	.741	.370	.539	1.857
	Month_Aug	.800	.076	.505	10.571	.000	.650	.950	.099	.741	.370	.535	1.869
	Month_Sep	.915	.076	.578	12.098	.000	.765	1.066	.201	.784	.423	.535	1.868
	Month_Oct	.834	.076	.527	11.036	.000	.684	.984	.131	.755	.386	.537	1.864
	Month_Nov	.608	.076	.384	7.959	.000	.456	.760	-.013	.639	.278	.525	1.905
	Month_Dec	.152	.077	.096	1.988	.050	.000	.305	-.392	.203	.069	.521	1.918

a. Dependent Variable: Ln_Sales

Table 8 | Variables introduced to multiple regression analysis 2 and their coefficients.

$$\begin{aligned}\mathrm{Ln}(salesvol) = {} & 9{,}946 + 0{,}028\mathrm{Ln}(subsidies) + 0{,}007consumerinterest - 0{,}004reintrosub - 0{,}005 \\ & + 0{,}054feb + 0{,}665mar + 0{,}769apr + 0{,}751may + 0{,}854jun + 0{,}798jul \\ & + 0{,}800aug + 0{,}915sep + 0{,}834\,oct + 0{,}608nov + 0{,}152dec\end{aligned}$$

The results, similar to those of model 1, confirm that subsidies are not influencing the solar collector demand. Moreover, the fit of the model improved from $\overline{R_2}$ = 0,160 to $\overline{R_2}$ = 0,869. The improvement can be explained because of the additional variables, which means that the model improved because now it considers the seasonality in the model. Hence, other variables, such as marketing expenses and prices of the product, should be included to have a better measure of the influence of the explanatory variables in the adoption of the solar thermal collectors – and therefore better predictions of sales.

Stage 7-8: Scoping the scenarios

Consumer Interest, as shown in the previous step, is a force that impacts sales the most and is highly uncertain. Therefore, this is the first critical force considered to formulate the scenarios around it. Moreover, after reviewing a just-released report about solar thermal collectors, by the IEA, the installation cost is selected as the second critical force. Thus, first the 2x2 table representing market acceptance – market stagnation and End-Consumer Interest – Final Purchase Price was developed, after creating the four plausible scenarios.

Socio-economic factors impacting end-consumer choice:

Most relevant factors	Best (1)	Worst (2)
(A)End-consumer Interest on STS	Interested and Ready to adopt / install STS	Not Interested and ready to adopt / install another RES technology
(B)Solar thermal system cost (driven by installation cost)	Decrease on installation cost, and therefore final purchase price too	Installation cost gets higher, and so final purchase price

Table 9: End-Consumer – Final Purchase Price / Market Acceptance – Market Stagnation

End-Consumer Interest on STS

Market Acceptance

Market Stagnation

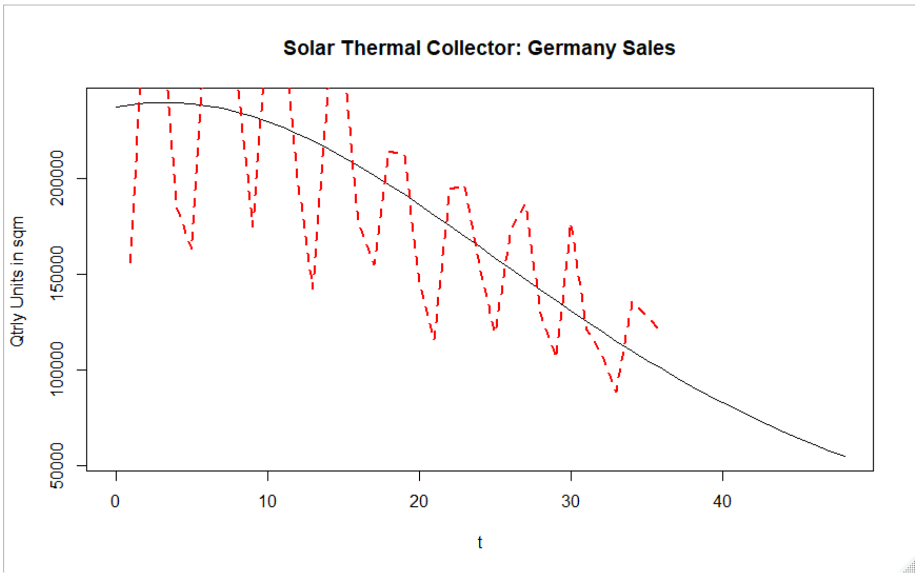
A1 –B1 Market Growth: End-consumer is ready to adopt and install STS, as final purchase price decrease	**A2 –B1 Market revitalization not materializing:** Although the final purchase price decreased, end-consumer prefers other RES
A1 –B2 Market Uncertainty End-consumer is interested on STS, however final purchase price is high (installation)	**A2 – B2 Market Stagnation:** End-consumer is not interested on STS, as final purchase price is high

STS final purchase price

Table 10: Final four scenarios developed

Stage 9: Diffusion of Innovation – Thresholds

Predicting when will the solar thermal collectors be self-reinforcing is the final step. This is with the idea to foresee if the product's sales will peak out soon, or to realise if this moment happened already. The Bass model was used to depict the product's likely diffusion pattern over time. As shown in the graph the peak of sales for the Solar Thermal Collectors was already in 2011-Q3. Looking at the p and q coefficients, it is implied that the adoption and innovation rates are very similar, which means that the product might be facing market saturation and, therefore, its slow diffusion. As a remark, the adoption curve is estimated with the data from 2010 until now. However, 2010 was the year when the company joined the Solar Thermal Market, and thus the information from previous year is not available. Moreover, considering the calculated m, which represents the eventual market, a quick comparison of the covered market is depicted.



Eventual/Potential Market (m) 8,607,303

Actual Sales/ Market 6,710,823

Peak of Sales 2011-Q3

Avg 8.4 m^2 installed per house in Germany.

Houses covered: 1,024,679 houses out of 42M

p: 0.02758505 q: 0.03360447 m: 8,607,303

Fig 6 Bass model estimation for Solar Thermal Collectors in Germany. Cumulative sales per quarter 2010 -2018, predicting to 2021.

The following table summarizes the followed steps and the techniques used:

Augmented IL Approach Steps	Data	Technique
Setting the scenario agenda	Germany Sales Volume 2010 – 2018	Extrapolation Forecasting: Least Squares + Seasonality
Determining the driving forces	Germany BRG market report and IEA – SHC country report	Influence Diagrams
Clustering of driving forces	Expert opinion	
Defining cluster outcomes	(DV) Germany Sales Volume 2010 - 2018 (IV) Predictors: - Re-introduction of subsidies (sqm) - Economic-aid (yes/no) - Consumer Interest (Google Trends Index)	Multivariate Regression
Impact/uncertainty matrix		
Framing the scenarios		
Scoping the scenarios		Critical Scenario Method
Developing the scenarios		

Identifying threshold for diffusion	Volume Sales thermal solar collectors 2010 - 2018: Germany	Bass Model

Table 11: Overview of Augmented IL Approach Steps, data, and techniques.

Discussion and Conclusion

The main objective of this study was to use the augmented intuitive logics theory to cope with the current environmental uncertainty that the solar thermal collector market in Germany is experiencing. Through this confirmatory-exploratory research it was found, regarding the literature reviewed and data employed, that the two critical forces which slow the adoption of solar thermal collectors in Germany are the awareness/knowledge of the end-consumer towards the technology (consumer interest) and the final price (cost) of the technology. On the other hand, subsidies, as expected, don't have an influence on the adoption of solar thermal collectors. The reasoning may be because of the findings of Jager (2006) and Huang et al. (2019) that either consumers are not aware of the incentives or that other technologies have better promotion.

Least squares with seasonality was applied to the time series successfully. This can be said as the predictions were validated with sample-out observations.

Google trends index was used as proxy measure of consumer interest, however there might be other keywords that represent better consumer interest towards solar thermal collector. Also, despite the fact that Google trends index is found in literature to improve the accuracy of prediction models, as suggested by Schaer et al. (2017), another disadvantage of incorporating this data in the model is the variation of the index from day to day, as it depends on the search frequency, making replication of experiment difficult.

The standard Bass Model was applied to the sales volume time series. Although this is common practice, other researchers have extended the model to improve the accuracy of prediction. For example, Fan et al. (2017) applied the Bass Model to historical sales data and online reviews to forecast product sales.

Regarding the Augmented Intuitive Logics theory, Derbyshire and Giovannetti (2017) proposed different techniques to develop scenarios, yet this research was conducted mostly with two main techniques: (non) linear least squares and the conceptualization stage of system dynamics.

Moreover, they aimed to contribute to the literature of scenario planning by proposing this novel methodology. However, after the conducted literature review, it can be concluded that the idea of combining qualitative techniques with quantitative was already proposed by ______ under the name of la prospective.

Finally, this research concludes that this Derbyshire and Giovannetti (2017) methodology should not be taken as a straight-through process, there might times when working the process partially might be equally useful. For instance, it was found in literature that usually system dynamics model and the Bass model are used together to develop scenarios. For example, Schmidt-Costa et al.

(2019), they used system dynamics model for a deeper understanding of incentive programs (leasing) to promote the adoption of photovoltaic solar collectors, and after they use the Bass model to estimate the adoption rate.

Recommendation

Although this study was carried in a high-level, the two main critical forces framed in this research speak for the microenvironment level, therefore future research needs to be done in order to understand end-consumers behavior and therefore, the diffusion pattern of solar thermal collectors. End-consumers' lack of knowledge and awareness of solar thermal collectors was one of the confirmatory results of this study. Hence, investigating whether households, know about solar thermal collectors and whether they will adopt the technology in the near future will help to cope with the uncertainty of market acceptance. The additional future study should be more consumer tailored, as Roveda and Vechiatto (2010) suggested that to fully understand the implications and consequences of critical forces they should be the starting point of a strategic analysis, which may result in reconfiguring the current industry value chain. As a basis, the work by Islam (2014) could be considered. He developed a discrete choice experiment to predict the diffusion of solar photovoltaic collectors. His research consisted in surving Canadian householders who did not have micro-generation technologies - yet - by asking them (1) their preferences for attributes of photovoltaic collectors, the (2) likelihood of adoption and when, if at all, will they adopt the technology. The findings resulted in recommendations for the content of adoption campaigns, as well as highlighting that word-of-mouth can work as a catalyzer for the technology adoption.

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Appendix

Validation

Validation is the final step to ensure that the results obtained from the regression models are useful (Hair et al, 2014).

STAGE 1 - Setting the scenario agenda

To validate the results of this stage, following Schazer et. al (2019), the Holt – Winters model has been applied to the sales volume time series used in this stage. Also, actual results have been obtained from the company. The following table shows the RMSE of both methods.

Method	Least Squares with Trend and Seasonality	Holt – Winters
RMSE	8,91	18072

		Forecast	Lower Limit	Upper Limit
FORECAST	2019	403.542	398.704	408.380
	2020	335.311	330.474	340.149
	2021	267.081	262.243	271.919

Forecast values

Solar portfolio	B'19	E'20	E'21
Domestic market data			
Solar thermal (sqm) total*2	**400.000**	**376.800**	**360.598**

Actual values

This suggests that the values obtained from the model using least squares with trend and seasonality are reliable.

Stage 4-6: Impact/Uncertainty matrix

To validate the results of the model used to estimate the impact of the forces on the sales volume, the data has been split into three different samples and ran the model again. The results are the following.

Model	**Approx. 75%**	**Approx. 50% (1)**	**Approx. 50% (0)**
n=	91	53	55
S.E.	.130	.166	.121
R^2	.912	.848	.929
Sig	.000	.000	.000

This table shows that the model holds even if the sample gets smaller, indicating that the model is fit for predictions.