Article

Combining business model innovation and model-based analysis to tackle the deep uncertainty of societal transitions – a case study on industrial electrification and power grid management

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Abstract: Creating new business models is crucial for the implementation of clean technologies for industrial decarbonization. With incomplete knowledge of market processes and uncertain conditions, assessing the prospects of a technology-based business model is challenging. This study combines business model innovation, system dynamics and exploratory model analysis to identify new business opportunities in a context of socio-technical transition and assess their prospects through simulation experiments. Furthermore, insights are visualized in a roadmap to coordinate action among the actors involved. This combination of methods is applied to the case of a business model aiming at ensuring stability of the electrical grid by centralizing the management of flexible loads in industrial companies. A system dynamics model was set up to simulate the diffusion of flexible electrification technologies. Through scenario definition and sensitivity analysis, the influence of internal and external factors on diffusion was assessed. Results highlight the central role of energy costs and customer perception. The chosen combination of methods allowed the formulation of concrete recommendation for coordinated action, explicitly accounting for the various sources of uncertainty. We suggest testing this approach in further business model innovation contexts.

Keywords: Prosumer concepts, technology change, business strategies, system dynamics, decentralization, photovoltaic, deep uncertainty, low-carbon transitions

1. Introduction

Climate change mitigation requires a transition to a low-carbon society, i.e. significant reductions of greenhouse gas (GHG) emissions. The decarbonization of the energy sector is decisive to this end [1]. Thanks to several effective climate policies and technological progress, the share of power generation stemming from renewable sources (such as solar and wind) has largely increased in the previous years, and an accelerated uptake of related technologies is expected for the future (BMWI, 2019). Additionally, major technological changes in the industrial sectors are necessary to achieve a low-carbon transition [3]. There are several pathways to reduce GHG emissions in the industry: adopting highly energy efficient technologies, implementing carbon capture and storage systems, and the electrification of production processes [4]. The strong penetration of renewables provides the necessary carbon neutral energy sources for a clean industrial electrification.

However, the increase of renewables and the electrification of industrial processes pose major challenges to the electricity grid. On the one side, the variability and unpredictability of renewables may compromise grid stability. Therefore, additional control measures and flexibilities on the level of the distribution grid are needed to maintain the balance between supply and demand [5]. On the other side, the electrification of industrial processes rises peak demand, thus increasing grid

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congestion and the need to upgrade grid capacity unless alternative measures are developed [6]. An interesting option is the use of digital technologies that enable smart solutions to deploy novel flexibilities. Smart controlling of electrification technologies contributes not only to decarbonization, but could also provide flexibility services to the grid, facilitating the integration of renewables by absorbing excess energy or decreasing the demand in peak hours. Likewise, smart control can mitigate congestion problems by reallocating the peak demand [7].

While many technological solutions exist for electrification, flexibility and smart grid control, a crucial step for their successful implementation is the formulation of appropriate business models [8], [9]. Business models play an important role in the transition dynamics: they not only support the diffusion of innovative technology but also enable coordination between different actors and thus act as an intermediate between the technological niche and the socio-technical regime [10]. Nowadays, energy-related companies need to continuously monitor for new opportunities to reconfigure their business model, to secure market shares, revenues and profits [8], [11]. Business model innovation (BMI) supports the transformation of traditional business models by identifying new opportunities. The process starts by understanding the changing environment, recognizing significant trends that can trigger important changes, and ends with integrating the innovative business model into the company and implementing the business idea [12].

However there exists high uncertainty regarding the impact of the changing business environment on market development and the long-term value creation of envisioned business models [13]. Thompson and Macmillan (2010) [13] state that "high uncertainty contexts give us the 'luxury' of specifying a priori what will and will not be acceptable" in order to save resources and to define appropriate key actions. However, in the early exploratory stage of business model conceptualization, managers face the uncertainty and unpredictability of fast-evolving markets and may have a biased mental model of the environment [14]. In addition, business models sometimes require coordination among different actors, each with their own interests, priorities and mental models. The situation in which decision makers are faced with multiple equally plausible futures and system models, termed “deep uncertainty”, calls for creative thinking and model-based decision support [15]. More generally, there is a research gap on the implementation, tools and challenges of business models [16]. In the specific context of the energy system, the ongoing socio-technical transition is a highly uncertain and complex environment for incumbent companies and new players. Several actors, such as energy utilities and distribution system operators, need to rapidly reconfigure their business model to adapt to this changing environment. According to several authors [8], [11], [17], [18], utility companies lack the business model innovation knowledge that helps to identify new opportunities within the energy transition. Decentralized renewable energy generation requires a different value proposition and revenue model compared to the existing centralized energy technologies.

To overcome these challenges of business model innovation, experimentation should be used to frame and understand the uncertainty of the business environment [19]. In the face of the high costs and limited feasibility of running experiments in the real world, simulation offers a low-cost alternative. For example, system dynamics (SD) is a methodology to map the interaction of many variables in complex systems and explore their behavior through simulation models [20]. In the context of business model innovation, SD has been shown to facilitate decision makers' understanding of the impact of environmental changes [21]. Indeed, the implementation of new business models depends not only on internal factors within the company but also on new regulations, uncertainties on the market and social acceptance. System dynamics can capture the relationship between internal and external factors and reflect realistic situations considering different political, economic and social circumstances [22]. This way, a clear action plan can be developed that helps coordinate the activities of different actors over time. SD has also been used to tackle deep uncertainty, using computational experimentation to yield insight from simulation models under imperfect system knowledge and uncertain future conditions [23]. To ensure that insights are transferred to practice, results of such business model simulations should be carefully communicated to all relevant actors, i.e. not only within the organization, but also e.g. to policymakers. Thus, a

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roadmap can help to effectively visualize the most important results and clearly communicate the required action points to the different actors [24].

This paper addresses the research-practice gaps on business model innovation (see above) by presenting a combination of three established fields of methods (BMI, SD and technology roadmapping (TRM)) to assess the prospects of a novel time-based business model at the energy-industry interface. This combined framework aims at helping multiple actors develop a qualified and consolidated a-priori understanding of the impact of the highly uncertain energy transition environment. The first steps consist of a market characterization and the definition of a concrete business model. Next, in a participatory process, a system dynamics model is developed to simulate the diffusion of flexible electrification technologies. To determine which factors have the greatest effect on the uncertainty of model outputs, two series of computational experiments are conducted: a scenario analysis, and a sensitivity analysis with statistical estimation of parameter importance. Based on the qualified understanding, a corresponding implementation pathway in the form of a technological roadmap is suggested to orchestrate the activities between multiple actors. The aim of this approach is to support experimental learning and co-creation of new value propositions in a cost-effective way. This methodical framework was applied to a time-based business model (described in section 3.1) aiming at avoiding grid congestion in a future of increased electrification. The main idea is to allow the use of redundant grid capacity (which is currently reserved to guarantee security of supply in the case of a failure of power lines) for specific loads with a certain degree of flexibility. The business model is targeted at industrial customers and requires the coordination of various actors: distribution system operator (DSO), utility, technology providers and policymakers. The environment also depends on uncertain exogenous factors such as future fuel and electricity prices, technology costs, as well as energy and climate policy. We use the proposed methodical framework to answer the following questions:

- Which circumstances favor or hinder the success of the time-based business model and the diffusion of flexible electrification technologies?
- Which are the main leverage points for the different actors to ensure the success of the business model?

The rest of this paper is structured as follows: Section 2 reviews the state of the research in the three methodologies combined in this study (BMI, SD and TRM); Section 3 presents the methods (description of the business model; system dynamics model and computational experiments; roadmapping); Section 4 the results; Section 5 discusses the implications of the results, as well as the methodological aspects of this study; Section 6 summarizes the method applied and the lessons learned from this first application, and formulates recommendations to the different actors.

2. Literature Review

We base our case study in the conceptual literature of business model development under uncertainty in the current context of sustainable transition from a fossil-based energy system. In this section, we briefly review the relevant methods of the forecasting literature that apply a dynamic perspective: business model innovation, system dynamics and technology roadmapping. The main uses and drawbacks of each method are summarized in Table 1.

Table 1: Main use and drawbacks of the three forecasting methods combined in this study.

	Purpose	Drawbacks
Business model innovation (BMI)	• Identify new threats and opportunities to the current business models • Support the establishment of new business ideas	• Difficult to coordinate different actors • When should action be taken?

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System dynamics (SD)	• Enable experimentation at low cost • Capture internal and external dynamics	• Model structure and results can be difficult to communicate
Technology Roadmapping (TRM)	• Representing expected changes in the business environment and the corresponding planned actions over time • Clear visualization of distinct phases and necessary action steps of the respective actors	• Just a narrative tool on indicated actions • Causal effects and sensitivity of the indicated actions are not clear • The performance of the planned actions cannot be assessed

2.1. Business Model Innovation in the Energy Transition

A business model describes how an enterprise creates value for specific customers with a positive financial profit equation. Business model innovation (BMI) is the process of creating and capturing new value by introducing a change on one or several components of an existing business model [25]. According to Frankenberger et al. (2013) [12], the BMI process consists of four different phases: initiation, ideation, integration and implementation. In the initiation phase, a preliminary assessment is performed to understand the changing environment and recognize significant trends that can trigger important changes. The ideation phase aims at generating new business ideas. In the third phase, ideas are transformed into viable business models and finally, in the last phase, the innovative business model can be implemented [12].

BMI is an important process in constantly evolving environments, where the primary business model gets challenged and thus needs to be adapted [26]. In this kind of context with often deep uncertainty, BMI is not a matter of anticipating and foreseeing of the future, but more a trial-and-error adaptation process, experimenting with variants of business model configurations [27]. Therefore, imagination, experimentation and ongoing learning are crucial in the development of novel business models [14], [28]. Experimentation with a business model is an iterative process that implies elaborating the initial value proposition into a viable business strategy, the implementation of the strategy, the incorporation of feedback from the environment, and the consequent modification of the business model [29]. Several case studies show that concurrent experimentation with different business models under uncertainty creates a variety of options that facilitate the long-term survival of a company [29], [30]. The authors suggest that such simultaneous experimentation is a crucial learning strategy to cope with uncertainty in a cost-effective manner. Simultaneous experimentation involves careful selection of related experiments and a combined approach of planning, action and learning.

2.2. System Dynamics and Exploratory Modeling

For BMI, conceptual representation (in written, pictorial, mathematical or symbolic forms) facilitates the understanding and communication of new business model ideas within the organization and between actors [31]. Simulation modelling is a valuable tool to assess the consequences of changes in business models through conceptual representation and simulation of virtual experiments [32]. System dynamics (SD) is a methodology combining graphical representation and mathematical modeling to understand the behavior of complex systems over time [20]. This technique allows to evaluate how a business strategy performs over time and what can be done to influence this performance [33]. SD models can capture the relationship between endogenous and exogenous dynamics, thus permitting the evaluation of a business project under different political, economic and social circumstances [22]. Therefore, SD models can be used to facilitate the experimentation phase of BMI [19] and improve the understanding of decision makers [21].

Often, modelers and decision makers have limited knowledge of the processes shaping the business environment. Also, when future prospects of a business model are evaluated, it is necessary to make assumptions on the evolution of external factors, for which widely varying scenarios might be equally plausible. Therefore, multiple possible model formulations and multiple possible futures exist, with often not enough information to assess their likelihood. This situation is referred to as "deep uncertainty" [15], [23]. In this case, models should not be treated as predictive tools, but rather as a way to explicitly examine modeling uncertainties [34]. Such an explorative approach to modeling consists of conducting visual or statistical analysis on an ensemble of model runs, where model structure, inputs and parameters are varied [34]. The value of such a model-based decision making approach lies in the capacity to answer questions such as "under which circumstances is a business model promising?" or "what is the range of plausible outcomes?" [23]. This explorative approach has been used in combination with SD in the context of future-oriented technology analysis [23] and socio-technical transformation of energy systems [35].

For an exploratory approach, Bankes (1993) [34] argues that simple, question-specific models are better suited than more complex models that aim at a highly disaggregated and detailed description of the system. Also, Ghaffarzadegan et al. (2011) [36] strongly recommend the use of small SD models to facilitate experimentation and to carve out critical insights. Ghaffarzadegan et al. (2011) [36] define a small model as a model consisting of few critical stocks and a maximum of eight feedback loops. As long as the model structure captures the most dominant feedback loops and stocks, it can be used to easily identify the most important leverage points of the system.

2.3. Technology Roadmapping

Technology roadmapping (TRM) is an extensively used planning approach that combines technology and business developments [37]. A roadmap is usually a visual tool that describes the current status of a technology, sets up a view of the future and identify the needed actions to reach the expectations [38]. TRM was initially applied at the level of individual companies to plan specific technologies and products. Nowadays, TRM has evolved and is also widely used to create political persuasion tools. TRM presents a simple framework that can assist policy makers to recognize action points in a complex system [24]. In our approach, we mainly used this method to visualize our recommendation for coordinated actions between policy, business and technology development.

3. Materials and Methods

In this section we develop the methodical framework and present illustrative outcomes of distinct methodical steps. Our study applies a case study design [39] contributing to a transnational research project, with the objective of designing and testing an innovative time-based flexibility business model (named the "Power Alliance" business model; see Section 3.1). This business model depends on the diffusion of flexible electrification technologies in the industrial sector. This project was carried out in four steps (Figure 1). After a literature review on the barriers and drivers for the electrification of industrial processes, concrete business models based on three use cases of flexibility technologies (power-to-heat, power-to-hydrogen and batteries) were determined during several workshops with project partners. The project partners were representatives of an energy company (taking here the role of technology and business developer), a distribution system operator (user of the time-based business model defined here), three pilot customers (industrial customers in the service area of the DSO), an information technology company (assisting in technology development) as well as the interdisciplinary research team. The ten project partners are considered as experts of the current and envisioned business field. Additionally, the feasibility of the business model from a regulatory point of view was ensured by seeking feedback from a trade association of the energy industry.

Next, a SD model was set up to simulate the diffusion of flexibility technologies. To assess the prospects of the proposed business model under various socio-economic and regulatory settings, two

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sorts of computational experiments were performed: scenario experiments and parametric sensitivity analysis. Finally, insights from the participative modeling process and computational experiments were visualized in the form of a technology roadmap, providing different actors (utilities, grid operators and policymakers) with recommendations on the coordinated action required to facilitate the electrification of the industrial sector.

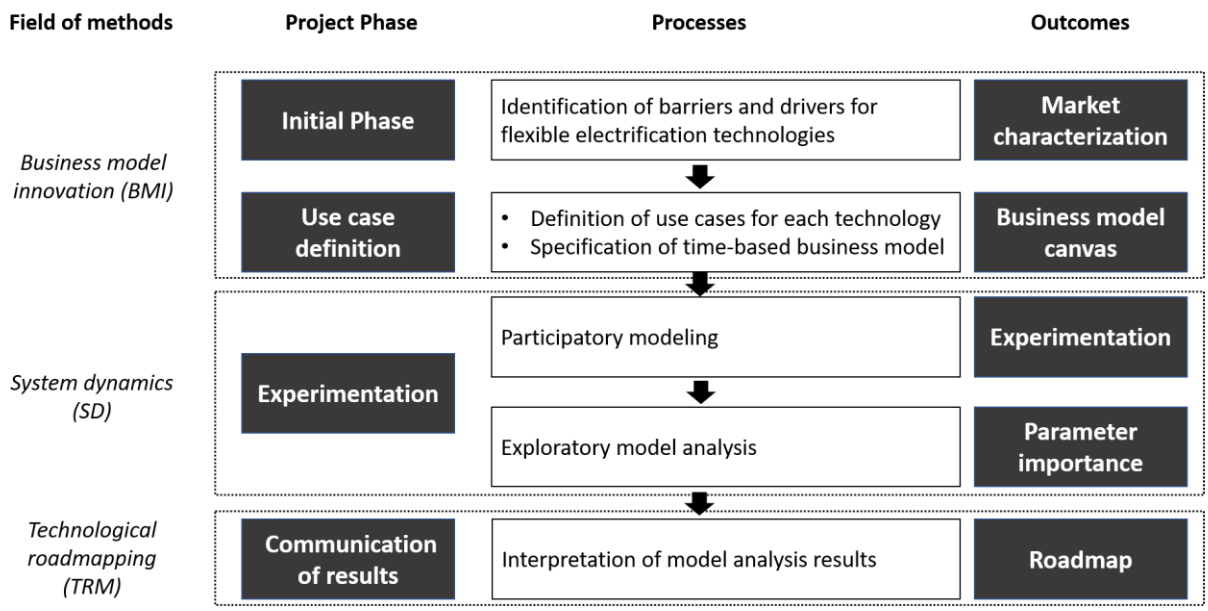

Figure 1: Method for the exploration of innovative business models under deep uncertainty.

3.1. Business Model and Use Case Specification

3.1.1. Characterization of the Business Environment, Drivers and Barriers

The first step in specifying the business model was to characterize the drivers and barriers for the electrification of the industrial sector, and the role that business models can play in assisting this process. The results of this assessment are summarized in Figure 1. A key driver of electrification in all sectors has been the increased power generation from renewable energy sources and the fast decrease of their cost [40]. The development of energy storage technologies has also greatly contributed to increased electrification, as they permit a better utilization of intermittent renewable energy sources. For some storage technologies, such as batteries or power-to-hydrogen, investment costs are projected to substantially decrease as the technology further matures [41], [42]. Sector coupling, i.e. the interconnection of electricity, heat, industry and mobility, offers various opportunities for decarbonization in the industry sector, e.g. by using hydrogen from renewable electricity to produce various chemicals [40] or by using battery capacity to provide grid frequency control and reserve capacity [43].

However, the use of electricity for industrial processes is nowadays limited for economic reasons [44]. Electricity is comparatively more expensive than natural gas, oil, or coal. The reason for this is twofold: first, the wholesale electricity price includes not only the energy use but also the grid cost, taxes and levies. Second, fossil fuel costs do not reflect their environmental impact, due to rather low CO_2 prices and the lack of an international agreement on a carbon tax [45]. As a result, the operational cost of electric technologies is not competitive with their equivalent fossil technologies, unless a tax reform is implemented [46]. Further barriers are related to the perceived utility of electrification, load management and flexibility technologies by industrial actors, e.g. concerns about financial and regulatory risk [47], lack of information, and lack of interest in participating in energy markets (“not-my-business” problem) [48].

Even if the potential of electrification in the industry is realized, new challenges might appear. Since massive electrification of industrial processes could increase peak electricity demand, this

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development, together with the large penetration of intermittent renewables, may compromise the stability of the grid and aggravate the grid congestion problems [6]. As a result, there will be a need to reinforce grid capacity, unless alternative measures are developed. An alternative is the use of digital technologies that enable smart solutions to deploy novel flexibility technologies.

To unlock this specific flexibility potential on the level of the distribution grid, new business models are required. The literature mentions several time-based flexibility business models that can be applied with the use of flexible technologies and smart grids. A classic example is the participation in the ancillary service market to provide frequency control and reserve capacity [43]. Batteries have been used for instance to reduce peak demand and profit from daily electricity price variations [49], [50]. The integration of renewables is another promising business opportunity. In this case, the utility can e.g. offer to the customers dynamic prices to incentivize the consumption of energy when large amounts of renewables are available, thus reducing curtailment [43], [51], [52].

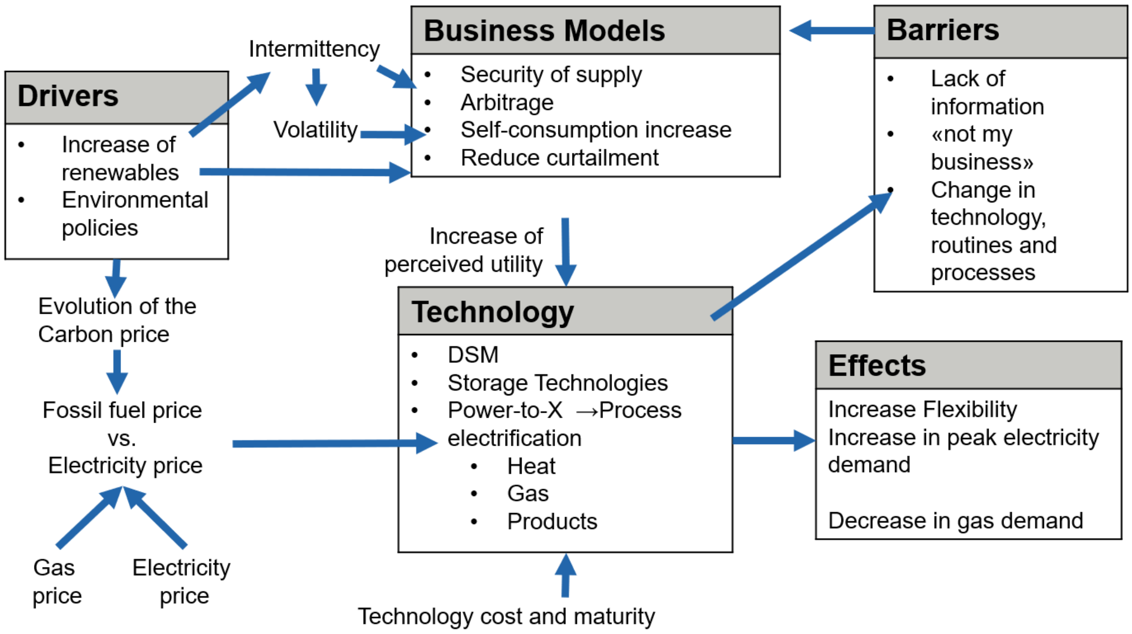

Figure 2: Barriers and drivers to the electrification of industrial processes.

3.1.2. The Power Alliance Business Model

The Power Alliance (PA) approach proposes a technical and economical scheme to avoid grid congestions under increased electrification. The main idea is to apply demand side load management only to a specific class of new flexible loads, the so-called "*conditional loads*", which mainly emerge from sector coupling applications such as power-to-heat installations and electrolyzers for hydrogen production. These loads exhibit a significant price elasticity and are more flexible in terms of usage due to a certain storage functionality. The PA business model presupposes that the currently redundant grid capacity used to provide today's high level of security of supply - the "*n-1 security*" – can be utilized by conditional loads, thereby attaining additional capacity in the existing grid infrastructure. Conditional loads are subject to a simple security of supply for a certain time span, while keeping the n-1 security for all other loads [53].

The PA business model requires coordination between different actors: distribution system operators (DSOs), utilities, technology providers, policymakers and industrial customers. From the perspective of DSOs, the main aspects of the business model are summarized on Figure using the canvas approach of Osterwalder & Pigneur (2010). This business model definition is the result of workshops with the project partners. The target customers are those on the electricity grid level 5 (medium voltage level; typically industrial customers) who installed or are thinking about installing a flexible electrification technology. The PA offer to these customers consists of a lower network tariff for their flexible loads, as well as the connection to a management system that optimizes the operation

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of their loads. The customers will be directly addressed and informed about the PA offer. This direct customer support will also be the main contact channel with the customers.

The DSO will profit by reducing the grid expansion need. Additionally, customers will pay connection charges. While lower than the standard tariff, the reduced grid tariff also contributes to the DSO's revenues. To offer this new product, there is a need of physical infrastructure such as the energy management equipment, and human capacity to advice customers, install and maintain the equipment. The key activity for the DSO is to provide consulting services to help customers understand the offer and find an optimal flexibility solution for their individual needs. The main costs are the infrastructure cost and the additional personnel cost for consulting services.

The actors involved have different incentives to participate in the PA scheme. For DSOs, the main incentives are a better plannability and control over their grid, as well as more detailed insights into grid flows, which allows them to offer attractive products. For grid customers, incentives to declare suitable loads as conditional loads comprise a significant reduction of grid fees for conditional loads (the "*Power Alliance Tariff*"), and an automated dynamic load management solution (the "*Regional Load Shaping*" solution; see Christen et al., 2019) [55] that minimizes the customers' energy costs for conditional loads according to stock prices whenever regional grid capacity constraints allow it. Policymakers and regulatory authorities are interested in testing and supporting technical solutions that promote flexibility and help to reach environmental and GHG reduction goals. Technology providers are interested in promoting the adoption of the flexible electrification technologies, whereas electric utilities are interested in offering innovative products to their customers, such as more exact energy consumption schedules to optimize the loads and energy costs.

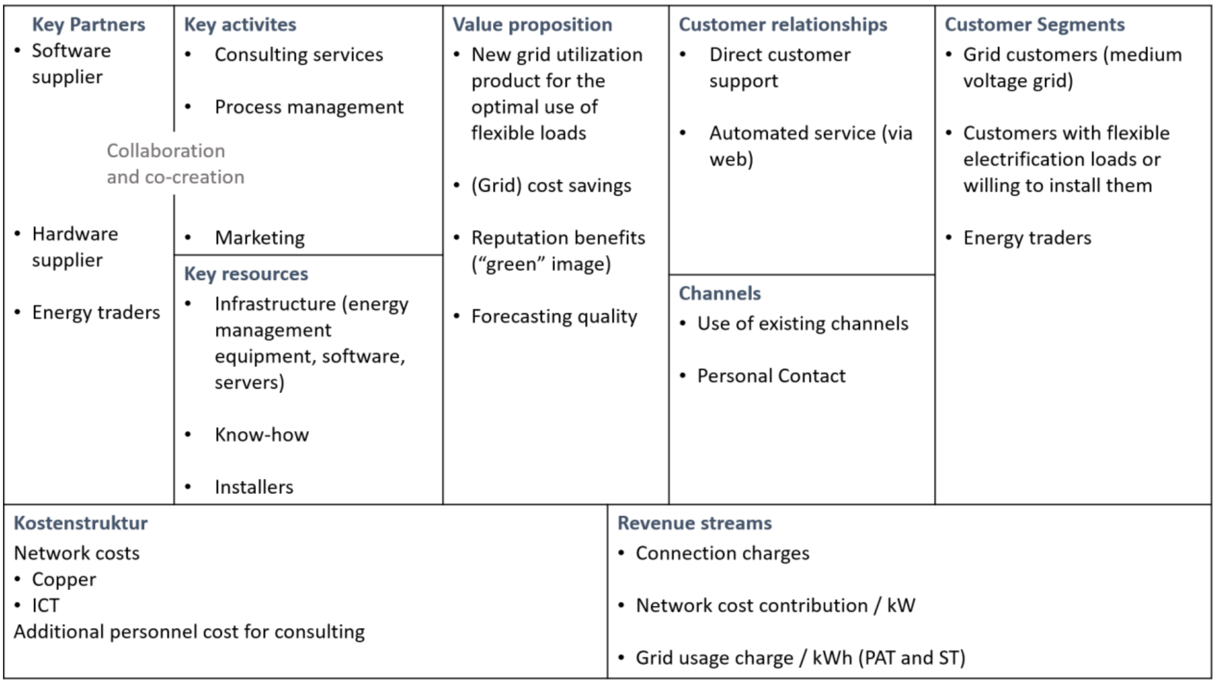

Figure 3: Canvas for the Power Alliance business model, from the perspective of the grid operator.

3.1.3. Use Cases for flexible Electrification Technologies

The Power Alliance business model is highly dependent on the diffusion of flexibility technologies such as batteries, Power-to-Heat and Power-to-Hydrogen. For this reason, the necessary conditions to adopt these technologies are studied in detail using a system dynamic model (described in Section 3.2.1.). For this analysis, three common use cases were selected to detail the financial advantages of the studied technologies as well as potential GHG emission reduction. These use cases were selected in workshops with members of an electric utility, a distribution system operator and

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industrial customers. In all use cases it is assumed that the self-consumed electricity has no cost. The most important assumptions of the three use cases are presented in Table 2 and described below. The market context of the use cases refers to Germany. A more detailed breakdown of the costs and revenues for each use case is given in Section 1 of the supplement.

The first use case, Power-to-Heat (PtH), considers the use of an electric boiler to generate heat in the paper industry (at a temperature requirement of about 120 °C). Electric boilers are a mature technology, with estimated investment costs between 100-400 € and an efficiency η_{P2Heat} between 97% and 99% [41]. The electricity can be obtained either from the electricity grid or from an installed photovoltaic system. The electric boiler can work together with an existing gas boiler (parallel operation) or independently. In parallel operation, the system can make use of the price difference between gas and electricity. A heat storage (such as a water boiler) is also considered to increase the flexibility of the system.

The second use case, Power-to-Hydrogen (PtH_2), assesses the usage of an electrolyzer to generate hydrogen as a raw material for the chemical industry. It is assumed that the electrolyzer replaces a Steam-Methane Reforming system that uses natural gas to produce hydrogen, releasing carbon monoxide and a relatively small amount of carbon dioxide. Due to economies of scale, it is expected that the cost of the electrolyzer decreases within the next years from almost 1500 €/kW in 2016 to 480 €/kW in 2050 [41]. The electrolyzer takes the electricity from the grid or from an internal source such as a photovoltaic system.

The last use case concerns the use of a battery storage to increase the self-consumption share of a photovoltaic system. The battery can also be used to provide services to the grid as part of the PA business model. Furthermore, the battery can take advantage of arbitrage opportunities, buying electricity from the grid at cheap prices and selling it when the prices are high again. The capital cost of the battery is assumed to be 1200 €/kWh in 2016 when the simulation starts and to decrease to 290 €/kWh in 2050.

Table 2: Use cases assumptions.

PtH		
Installed capacity	500 kWe	
Investment cost	100 €/kW	[41]
Life time	30 years	[41]
Efficiency	98 %	[41]
Efficiency of the replaced boiler	98%	[56]
PtH_2		
Capacity of the water electrolyzer	500 kW	
Investment cost @2016	1500 €/kW	[41]
Investment cost @2050	480 €/kW	[41]
Life time	30 years	[41]
Electricity consumption per kg H2	55 kWh/kg	[57]
Gas needed per Kg H2 for the replaced SMR	40 kWh/kg	[58]
Batteries		
Installed capacity	500 kWe	
Investment cost @2016	1192 €/kWh	[42]
Investment cost @2050	289 €/kWh	[42]
Life time	20 years	

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Charging time	1 hour	

3.2. System Dynamics Simulation

3.2.1. Model Structure

The SD model simulates the diffusion of flexible electrification technologies and the adoption of the PA offer in a local distribution grid with 45 industrial customers (Figure 4). The model simulates the diffusion of one technology at a time. The core of the model consists of three state variables, each of them representing the number of customers subscribing to a certain offer. At the beginning of the simulation, there is no flexible technology ("Flexloads") installed, thus all customers belong to the stock "Customers without Flexloads". At each time step, a certain fraction of the customers may decide to switch to one of the alternative options. One possibility is to install a flexibility solution, without subscribing to the load management program of the utility. Customers who choose this option are still subject to the standard grid tariff (ST). Alternatively, customers may choose to participate in the regional load shaping program and benefit from the Power Alliance Tariff (PAT). The switch to the PAT may happen either directly (customers install a flexibility solution and join the regional load management program at the same time), or indirectly by first installing a flexibility solution, and in a second step, deciding to join the load management program. In each customer stock, a fraction of the customers has their own renewable energy source (RES). For the stock "Customers without Flexloads", the fraction of customers with RES is updated according to the chosen scenario (see Sect. 3.2.2.), simulating the percentage of renewables in the total energy consumption as a proxy.

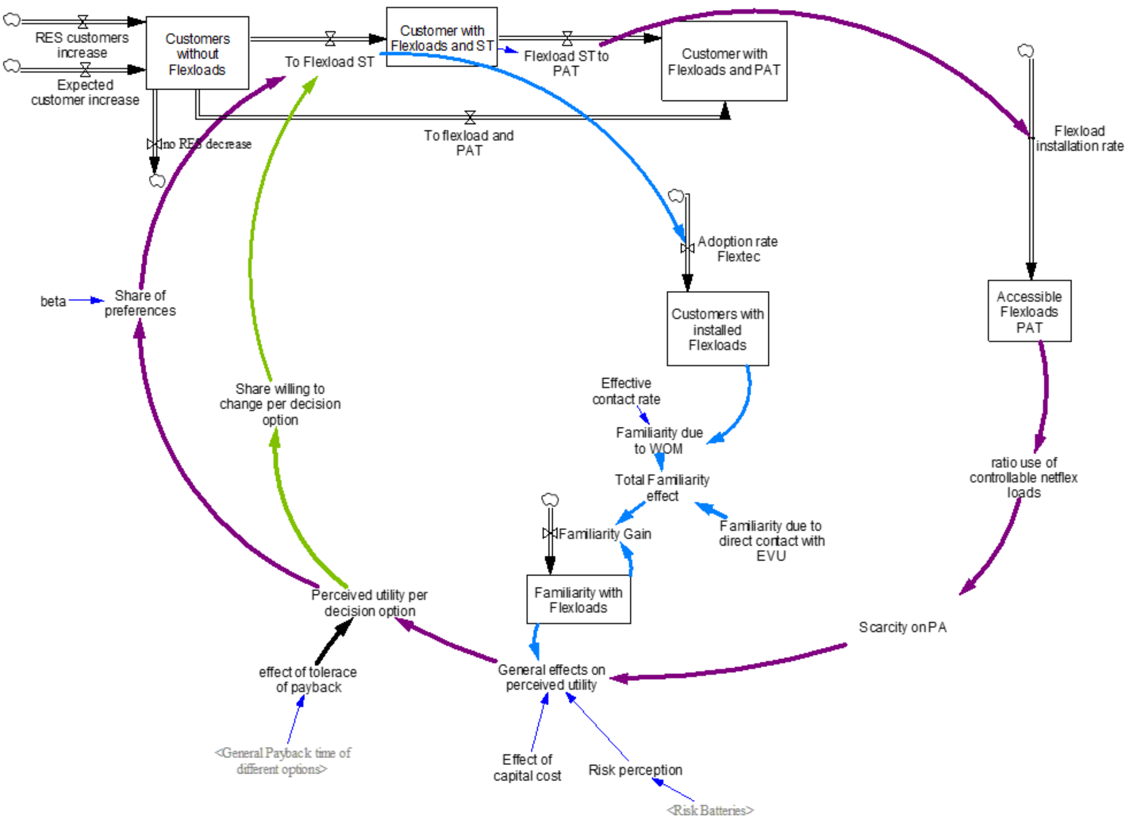

Figure 4: Structure of the system dynamics model representing market dynamics at the scale of a local distribution grid. Boxes represent stocks, i.e. state variables; double arrows with valves represent flows, i.e. changes of the values of stocks; simple arrows represent causal relationships.

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The core loops of the model, shown on Figure 4, share a similar structure with the model developed by Kubli (2018) [59] to study the diffusion of decentralized photovoltaics. The number of customers moving from one option to another at each time step, following the flows on Figure 4, depends on the perceived utility of each decision option, as well as on the specified adjustment times (AT) for each possible switch. The factors influencing perceived utility are described below. ATs are time constants accounting for delays in the system. Indeed, it is unrealistic to assume that all customers willing to install a flexibility solution will do so immediately. Many factors may delay this decision for an individual customer, such as financial, time and knowhow constraints, or organizational structures and processes. The ATs control the rate of change as follows:

$$r_{i,s,t} = r_{pot,i,s,t}/AT_i \ , \qquad (1)$$

where i represents the different type of customers ($i \in$ {customers without flexloads, customers with flexloads and ST, customers with flexloads and ST }), and s distinguishes the customers with and without renewables installed ($s \in$ {customers without renewables, customers with renewables}), consequently $r_{i,s,t}$ is the rate of customers changing from option i_0 to option i at time step t [Customers/year], $r_{pot,i,s,t}$ is the number of customers planning to change from option i_0 to option i , and AT_i the adjustment time [years] corresponding to this transition.

The model considers six decision options, each corresponding to one of the flows in Figure 4 (each flow symbolizes two distinct decision options, for customers with and without RES). At each simulation time step, the model calculates the attractivity of each decision option, expressed as the share of potential customers willing to change. This attractivity depends on the perceived utility of each decision option, which in this model depends on financial aspects (payback time), social aspects (familiarity of flexible technologies and customers' willingness to invest) and a scarcity effect. The share of customers that choose each option $\boldsymbol{f_i}$ is determined using a logistic function:

$$f_i = \frac{1}{1+exp[-\beta(u_{i,0}-u_i)]} \ , \qquad (2)$$

where u_x is the dimensionless utility function corresponding to each decision option x, $\boldsymbol{u_{i,0}}$ is the perceived utility of the current concept and $\boldsymbol{u_i}$ is the perceived utility of the competing consumption concept. β is an empirical shape parameter. The perceived utility u_x of a decision option is calculated as follows:

$$\boldsymbol{u_x = f_{payback\_time} \times f_{capital} \times f_{familiarity} \times f_{scarcity}} \ , \qquad (3)$$

where all variables are dimensionless. The empirical functions used to estimate $f_{payback\_time}$, $f_{capital}$ and $f_{scarcity}$ are described in Section 2 of the supplement.

Familiarity S_{fam} is a state variable of the model and consists of two processes: the effect of word-of-mouth as a technology becomes more common, and the effect of customer relationship management by the utility. Familiarity may take values between zero and one and is initially set to 0.25 here. At each time step, S_{fam} is updated as follows:

$$\boldsymbol{\frac{dS_{fam}}{dt} = (f_{WOM} + f_{CRM}) \times (1 - S_{fam})} \ , \qquad (4)$$

where f_{WOM} is the effect of word-of-mouth in the current time step, and f_{CRM} the effect of customer relationship management. The latter is assumed to be constant, whereas the effect of word-of-mouth increases as the number of customers with installed flexibility technologies increases:

$$\boldsymbol{f_{WOM} = \frac{C_{flex}}{C_{total}} \times r_{contact}} \ , \qquad (5)$$

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where C_{flex} is the number of customers with a flexibility solution installed, C_{total} the total number of customers and $r_{contact}$ the effective contact rate [-]. This formulation for technology diffusion was introduced by Struben and Sterman (2008) [60].

The annual cash flows in the model are the sums of costs and revenues (from the perspective of the customer) related to the installed flexibility technologies. For each use case, the breakdown of costs and revenues is given in Sect. 3.1.3. and Sect. 1 of the supplement. An important factor for the economic viability of flexible technologies are future prices for electricity and natural gas (the latter only for the PtH and PtH2 cases). These are outside the system boundaries and assumed to increase as a function of time:

$$\boldsymbol{P}_{y,x} = \boldsymbol{P}_{present,x} \times (\mathbf{1} + \boldsymbol{b}_x)^{(y-2015)}, \quad (6)$$

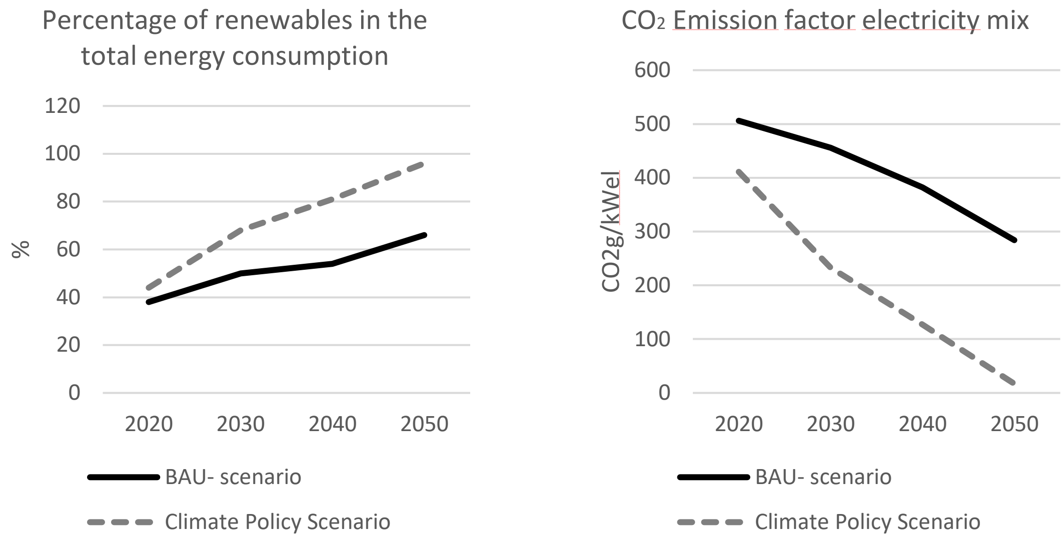
where $P_{y,x}$ is the price for either gas or electricity (represented here by x) in the year y, $P_{present,x}$ is the current price for x, and b_x is an x-specific parameter. The current (2016) prices for electricity (energy price only) and gas (excluding the carbon tax; see next section) were set to 0.04, and 0.03 €/kWh, respectively. The annual price increase for electricity, b_{el}, is set to a default value of 3%, and the annual price increase for natural gas, b_{gas}, is set to 2%. The breakdown of the wholesale prices for electricity and natural gas is given in Section 3 of the supplement.

The model was built and executed using the software Vensim DSS, version 7.3.5. The simulation period goes from 2015 to 2050, with a simulation time step of 0.0625 years. Numerical integration uses the explicit Euler method.

3.2.2. Scenarios

As the diffusion of the studied flexible technologies largely depends on uncertain climate policies, this work considers the application of two different climate scenarios. These scenarios are based on forecasts for the German energy market [45], [61]. This Section gives an overview of the scenarios, and the reasoning behind them is further detailed in Section 3 of the supplement. The first scenario, the business as usual (BAU) case, assumes that no tax reform or any other additional measure is adopted to promote decarbonization. Thus, the percentage of renewables in the total energy consumption reaches only 60% by 2050 and the CO_2 emission factor of the German electricity grid is approximately 300 gCO2/kW$_{el}$. Furthermore, as of today in Germany, no CO_2 price is charged for the use of gas as heating fuel. The Renewable Energies Act (EEG) surcharge, levied on electricity consumption to finance the development of renewable energy, starts at 6 €c/kWh and is phased out gradually to reach 0.8 €c/kWh by 2050, following the forecast of [62].

The second scenario assumes that strong policies measures are taken to support decarbonization and sector coupling. As a result, the Paris climate goals will be reached by 2050 in Germany, i.e. almost 100% of the total energy consumption can be met by using renewable energies. The CO_2 emission factor of the electricity mix is 17 CO_2g/kW$_{el}$. To reach these goals, it is assumed that a tax reform is applied, in this case a CO_2 tax (P_{CO2} [€/kW]) is charged to the natural gas and a tax reduction for electricity is implemented. Concretely, the EEG surcharge is reduced to 0.05 €c/kWh. The aim of this policy is to promote the use of green electricity and charge fossil fuels for their CO_2 emissions. Figure 5 illustrates the evolution of the scenarios over time, whereas Table 3 summarizes the most important assumptions.



a) b)

Figure 5: a) Percentage of renewables in the total energy consumption for the considered scenarios b) CO2 emissions factor of the German electricity grid.

Table 3: General assumptions of the two analyzed policy scenarios.

		BAU Scenario		**Climate Policy Scenario**	
		2030	2050	2030	2050
CO_2 electricity mix emission factor[1]	CO_2g/kW$_{el}$	506	284	411	17
Percentage of renewables in the total energy consumption[1]	%	38	66	44	96
CO_2 price on gas[2]	€/kWh	0		0.01 (45 €/TonCO_2)	
Electricity tax reduction (tax reform)[2]	€/kWh	0		Up to 0.077 (see supplement)	

[1][61]

[2][45]

3.2.3. Sensitivity Analysis

Many of the parameters used in the simulation models are subject to high uncertainty. This uncertainty arises for various reasons: first, the simulation period lies mostly in the future, so that it is necessary to make assumptions regarding the future evolution of energy prices, technology costs and taxes. Second, some parameters act as proxies for processes not explicitly represented in the model, such as the adjustment times (Eq. 1). This makes it difficult to constrain these parameters,

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especially in the absence of historical data that enables the calibration of the parameters. As some of the process formulations used here are widely used in SD, earlier studies give an estimation for the values of the corresponding parameters. However, these studies may apply to an entirely different context, so that transferring parameter values to a new study may be challenging. For example, most of the empirical values for the familiarity parameters come from studies on vehicles or consumer goods [60]. While these values give a rough indication of the possible parameter range, it is unclear how well they describe the attitude of industrial customers regarding their electricity consumption.

To assess the uncertainty in model outcomes and to identify the most sensitive parameters, a global parametric sensitivity analysis was conducted. The aim was to characterize the spread in model results under varying parameter values, as well as a measure of importance for each parameter. The target output variable is the number of customers that have installed a flexibility technology, a PV module and subscribe to the PA tariff at the end of the simulation ($C_{full,2050}$). In a first step, 2000 combinations of parameter values were generated, where the value of each parameter was varied within its plausible range. The parameters and their range are listed in Table 4. These sets were generated with the Latin Hypercube Sampling method, a stratified Monte Carlo scheme.

In a second step, parameter importance was assessed by fitting a random forest model [63], with the parameter values as predictors and $C_{full,2030}$ as the dependent variable. Such a meta-modeling approach to parametric sensitivity analysis provides a ranking of parameter importance, and the possibility to evaluate the effect of different parameters graphically [64]–[66]. Among the different measures of parameter importance provided by the random forest algorithm [63], the mean decrease of accuracy was used. This measure describes the loss of model performance when the values of one parameter are randomly shuffled, i.e. converted to noise.

Table 4: List of parameters varied in the sensitivity analysis, with their respective ranges and default values. For the parameters that appear in the model description in this report, the corresponding equations are indicated. For the other parameters, please refer to the description of the business models (BM) in Annex 4.3.

Symbol	**Meaning**	**Units**	**Minimum value**	**Maximum value**	**Default value**	**Eq.**
Common parameters						
$P_{grid,ST}$	Standard network tariff (ST)	€/kW	50	100	70	BM
f_{PAT}	PAT, as a fraction of ST	Dmnl	0.1	1	0.1	BM
$P_{inv,smart}$	Investment cost smart control	€	100	500	300	BM
$H_{running}$	Running hours per year (P2Heat and P2H2 only)	hours/year	3000	7000	6000	BM
b_{el}	Annual percentual electricity price increase	Dmnl	0.02	0.04	0.03	8
$d_{Pel,min}$	Min electricity price difference	€/kWh	0	0.04	0.04	BM

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$d_{Pel,max}$	Max electricity price difference	€/kWh	0	0.1	0.07	BM
AT_{load}	AT flexible loads	years	5	20	15	1
AT_{PAT}	AT smart control	years	1	5	2	1
β	Shape parameter for the function linking utility to preference	Dmnl	4	8	6	2
$r_{contact}$	Contact rate	Dmnl	0.1	0.3	0.2	7
l_{CRM}	Effect of customer relationship management by utility on familiarity	Dmnl	0.05	0.15	0.1	6,7
P2Heat parameters						
η_{P2Heat}	P2Heat efficiency	Dmnl	0.97	0.99	0.97	BM
b_{gas}	Annual percentual gas price increase	Dmnl	0.02	0.03	0.02	8
Battery parameters						
P_{FIT}	Feed-in tariff	€/kWh	0.03	0.12	0.08	BM
η_{Batt}	Battery efficiency	Dmnl	0.7	0.9	0.7	BM
P2H2 parameters						
P_{H2}	Hydrogen price	€/kg	4	12	8	BM
η_{H2}	Electricity consumption per kg hydrogen	kWh/kg	50	60	55	BM

A crucial step of a parametric sensitivity analysis is the choice of a distribution for each parameter [67]. Here, a uniform distribution was chosen for all parameters, with the range set as reported in Table 4. Two parameters describe the PA business model: the standard network tariff (ST) and the fraction f_{PAT}, which defines the ratio of PAT and ST. The ranges for the standard grid tariff $P_{grid,ST}$ and the investment costs for smart control $P_{inv,smart}$ were chosen based on scenarios provided by the project partners. The bounds for f_{PAT} were kept wide, ranging from no discount at all ($f_{PAT} = 1$ and PAT = ST) to an aggressive strategy where PAT is only 10% of ST. The parameter b_{el}, representing the annual percentual change of energy price, was varied so that the resulting prices stayed within the bounds of existing forecasts [62], [68], as shown in Figure 6. The parameters $d_{Pel,min}$ and $d_{Pel,max}$ reflect the volatility of electricity prices. The minimum and maximum values were selected based on scenarios provided by the project partners.

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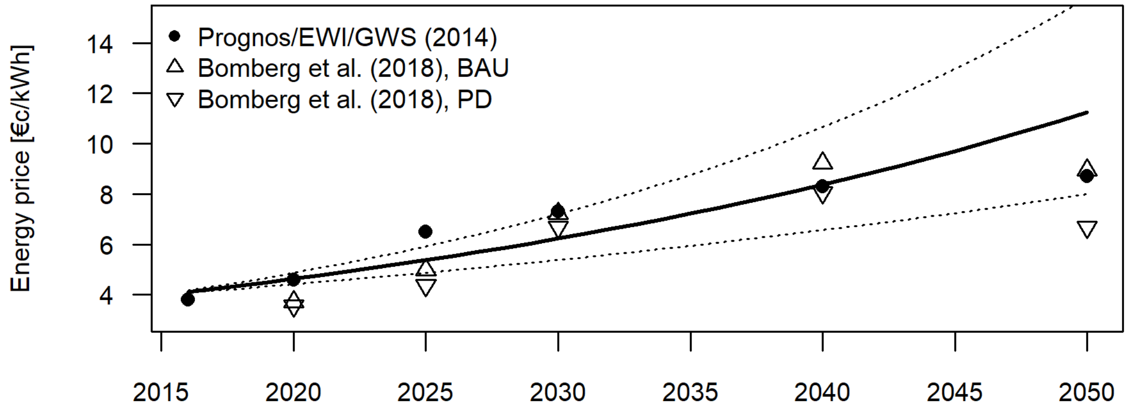

Figure 6: Future evolution of energy price. The solid line shows the future price calculated with Eq. 8, using the default parameter value for the annual increase (3% per year). The stippled lines show the development with minimum and maximum parameter values.

Values for parameters such as the adjustment times are typically obtained through calibration. As this study is concerned with business models that have not yet been implemented, there is no historical data available for calibration. Therefore, to define the range for these parameters, it is necessary to consider previous studies. For example, Kubli (2018) [59] obtained adjustment times between 1 and 4 years for the installation of photovoltaic panels by industrial customers. Here, the AT for the installation of smart control (AT_{PAT}) was varied between 1 and 4 years. It was assumed that, as the installation of flexible loads represents a much greater investment, the corresponding adjustment time (AT_{load}) is much longer (5 to 20 years). Values for the parameter β were also obtained through calibration by Kubli (2018), and ranged between 4.7 and 13 for industrial customers. For the two familiarity parameters l_{WOM} and l_{CRM}, Struben & Sterman (2008) suggest ranges of 0 - 0.3 and 0 - 0.02, respectively. These values are based on previous studies on consumer goods and do not necessarily describe the situation examined in this study. First, industrial customers probably behave differently from private customers and are likely more receptive to marketing efforts if the product can help their business. Second, due to the small market size, the utility can easily reach all its customers. For these reasons, the range for l_{CRM} was set substantially higher.

3.2.4. Model Validation

To acquire confidence in the model, several workshops with practitioners were performed. In these workshops, our industrial partners verified the structure and the most important parameters of the model. We had the opportunity to corroborate the existence and importance of the different feedback loops for the real-life situation of our case study. However, due to the lack of historical data, a detailed validation of the model was not possible. Nevertheless, we verify the response of the system to extreme conditions and perform sensitivity tests as reported in Section 3.2.3. Finally, we also validated the results with practitioners and ensured that the behavior projected by the model is likely and could be explained.

4. Results

4.1. Simulation Results

For the PtH case, Figure 7 a) and b) show the development of installed flexibility capacity in the grid for the two scenarios (BAU and climate policy (CP)) and two different assumptions on the percentage of electricity consumption stemming from the customers' own renewable generation (f_{renew}, 60% and 80%). To give a sense of the importance of these new technologies, installed flexibility capacity is expressed here as a percentage of peak demand. The fraction f_{renew} has a

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greater influence on the diffusion of PtH in the BAU scenario than in the CP scenario, since as mentioned before, the model assumes that the energy coming from own renewables has no cost. Consequently, the profitability of PtH increases with the percentage of own RES. Under the CP scenario, as the wholesale price is decreased for electricity and increased for natural gas, PtH is more competitive. Therefore, the percentage of renewables only has a marginal impact. The GHG emissions savings (Figure 7 c) and d)) are expressed as a percentage of the total emissions from process heating if all customers in the grid used a gas boiler. Clearly, the savings are larger in the CP scenario, where the electricity mix has a very low emission factor at the end of the simulation period.

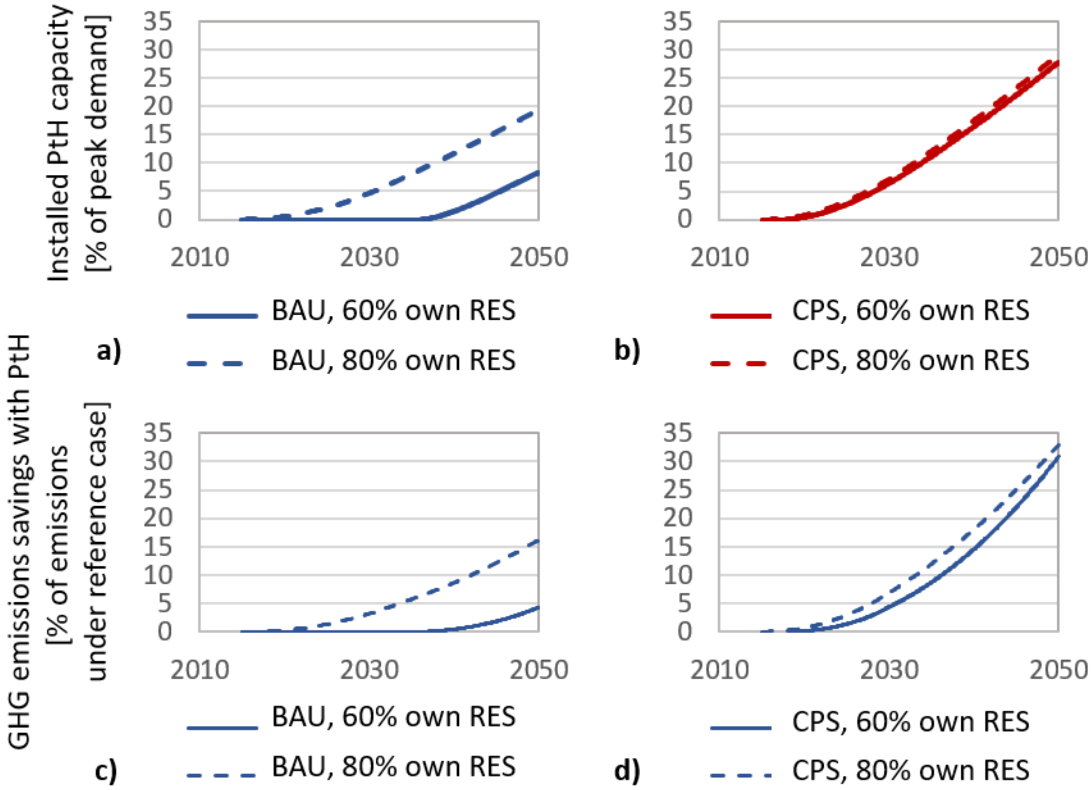

Figure 7: a) and b) Installed PtH capacity, expressed as a fraction of peak demand in the local grid, for the BAU scenario (a) and the CP scenario (b), with different percentage of electricity consumption from own renewable sources. c) and d) GHG emission savings in the PtH case, expressed as a percentage of emissions in a hypothetical case where no customers switch from a gas boiler to PtH.

The diffusion of PtH_2 (Figure 8 a) and b)) shows that the BAU scenario is not favorable to the diffusion of this technology. The situation changes somewhat under the CP scenario, but only if a large share of own renewables is available on site to cover the PtH_2 electricity demand. Consequently, the GHG emission savings (Figure 8 c) and d)) are also small or inexistent. As for PtH_2, installed capacity is expressed as a percentage of peak demand in the grid, and emissions savings as a percentage of the emissions that would occur if none of the customers switched from the reference case (steam methane reforming) to PtH_2.

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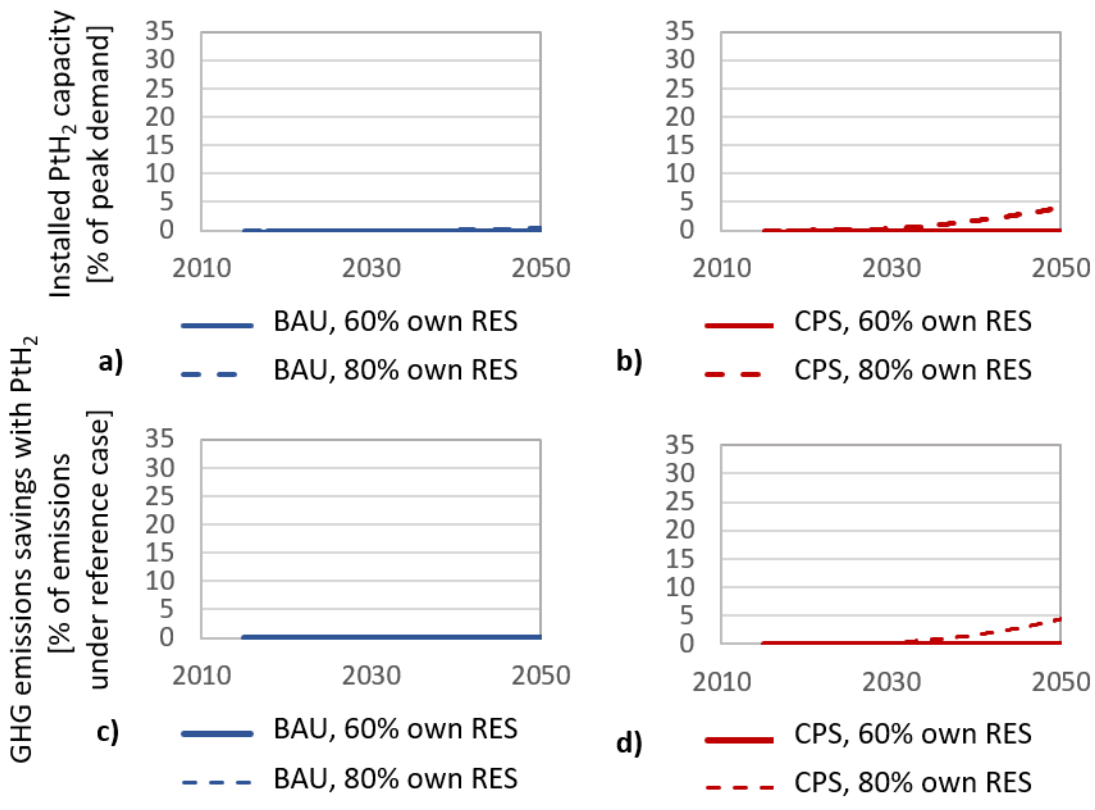

Figure 8: a) and b) Installed PtH_2 capacity, expressed as a fraction of peak demand in the local grid, for the BAU scenario (a) and the CP scenario (b), with different percentage of electricity consumption from own renewable sources. c) and d) GHG emission savings in the PtH_2 case, expressed as a percentage of emissions in a hypothetical case where no customers switches from steam methane reforming to PtH_2.

For batteries (Figure 9), the diffusion takes place slightly faster under the BAU scenario at the beginning of the simulation. This is because in this scenario, the price of the electricity coming from the grid is higher and thus the self-consumption business model is more profitable. With time, the penetration of renewables in the CP scenario is very strong and thus the associated installed battery capacity is larger than the BAU scenario. As the use case for batteries does not entail the substitution of another technology and is therefore not based on a comparison with a reference case, GHG emission savings could not be calculated.

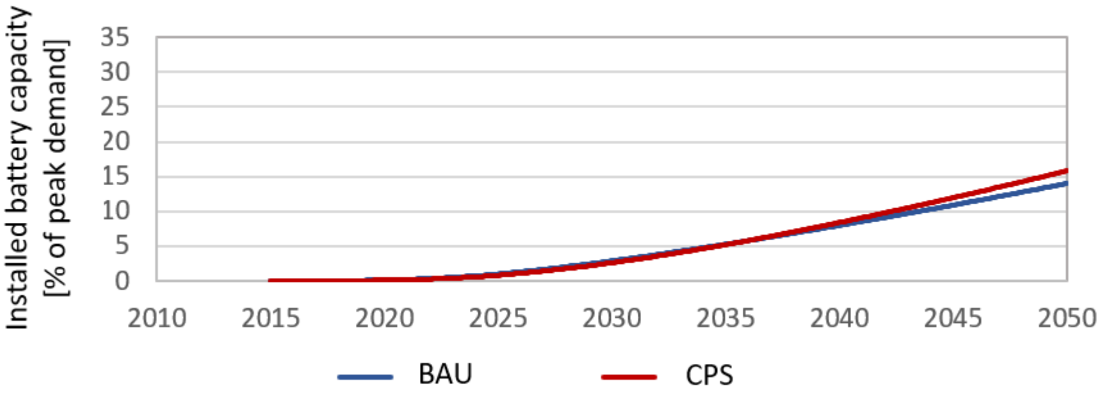

Figure 9: Installed battery capacity, expressed as a fraction of peak demand in the local grid, for the BAU scenario and the CP scenario.

4.2. Sensitivity Analysis

As shown in Figure 10, the speed and extent of the diffusion of flexibility technologies and the PAT offer differ greatly depending on technology, scenario and parameter values. For PtH, under the BAU scenario, many simulations lead to zero customers until the end of the simulation, while some simulations reach a number of 19 customers (out of 45 potential customers in the simulated market). Under the CP scenario, there are fewer simulations with zero customers, and the simulations with the greatest number of customers reach a number of 28. In some simulations, the onset of customer growth occurs quite late. For PtH_2, there is barely any customer growth in the BAU case, and only in a few simulations in the CP case. But even under this scenario, there is hardly any growth in the first 10 simulation years. For batteries, the spread between simulations is again rather large, with a substantial number of simulations with zero customers under both scenarios, and final numbers of up to 19 and 22 customers under the BAU and CP scenarios, respectively.

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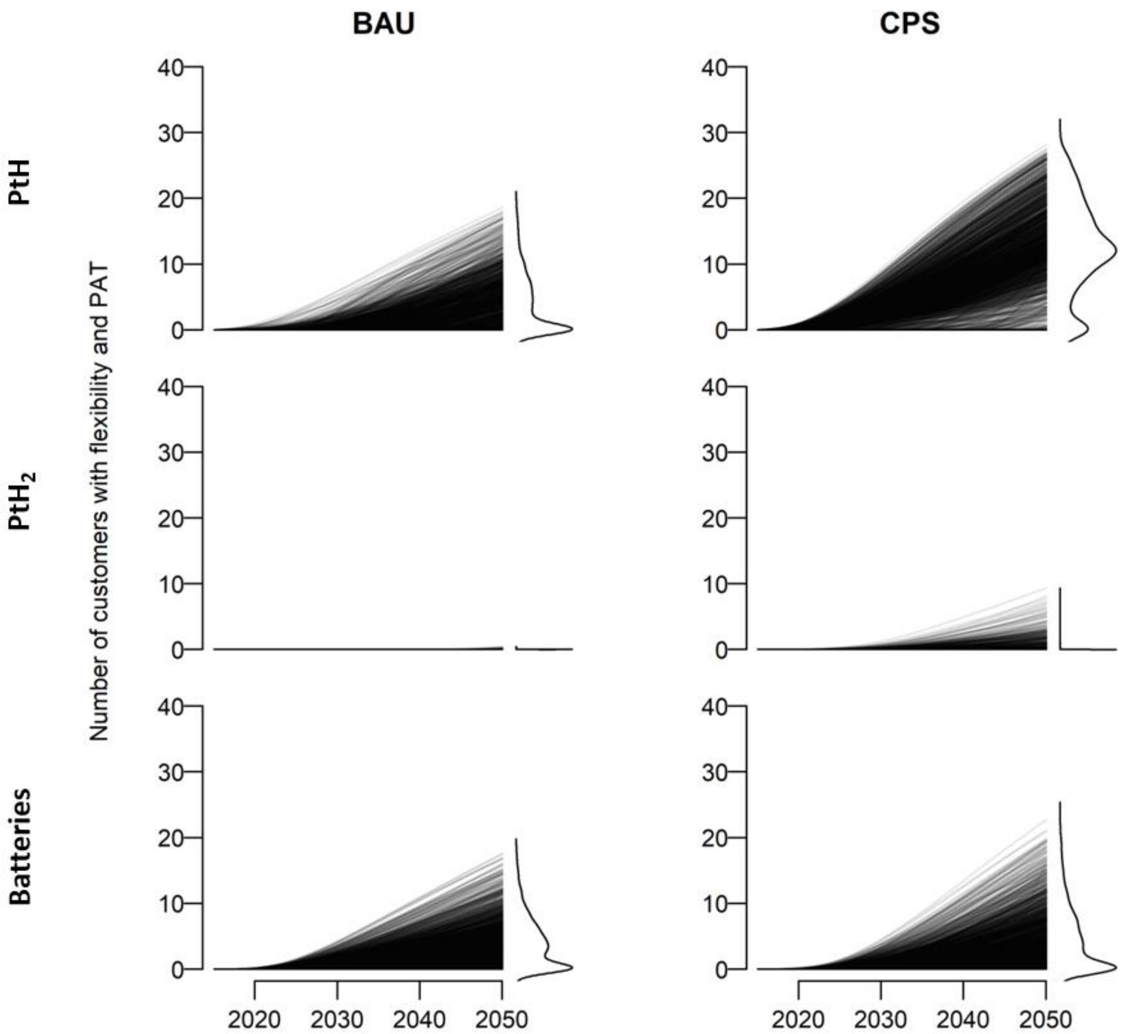

Figure 10: Evolution of the number of customers having installed flexibility and subscribed to PAT in the 2000 sensitivity runs. The line to the right of each plot shows the kernel density estimate for the number of customers at the end of the simulation period (2050).

The random forest algorithm calculates an estimation of the percentage of variance of the dependent variable explained by the model (see Liaw and Wiener, 2002). For the meta-models used in the sensitivity analysis, these scores are reported in Table 5. In most cases, the meta-models explain a large percentage of the variance of the dynamic model outputs, meaning that they appropriately capture the influence of parameter values on the output. However, in the case of PtH_2 under the BAU scenario, this score is very low, since the number of customers at the end of the simulations is zero in nearly all simulations. For this reason, the sensitivity analysis was not carried out for this case.

Table 5: Percentage of the variance of model outputs explained by the random forest meta-models

	BAU	**CPS**
PtH	94.82 %	86.55 %
PtH2	6.07 %	69.18 %
Batteries	84.39 %	84.17 %

For the presentation of parameter sensitivity scores on Figure 11, parameters were divided into two categories: "hard" parameters, representing technological and economic factors, and "soft" parameters, related to decision-making. This distinction is only represented graphically and had no influence on the meta-modeling process.

For PtH under the BAU scenario, the most important parameter is f_{renew}, the percentage of electricity consumption that can be covered by self-consumption of electricity produced on site from renewable sources. The next two parameters belong to the "soft" category and describe the delay in adoption of flexible technologies ($AT_{load,res}$) and the influence of direct marketing by the utility (l_{CRM}). The grid tariff reduction factor under the PA offer (f_{PAT}) and the annual energy price increase (b_{el}) are also somewhat important, while the other parameters have little to no influence on model results. Under the CPS scenario, while f_{renew} is still important, $AT_{load,res}$ becomes the most influential parameter. The CO_2 tax P_{CO2}, which is set to zero in the BAU scenario, is also quite influential under CPS. For PtH_2, the three most influential parameters belong to the "hard" category, i.e. f_{renew}, P_{CO2} and the number of running hours $H_{running}$. For the "soft" parameters, $AT_{load,res}$ is of intermediate importance and l_{CRM} has little influence. In the case of batteries, there is little difference in parameter importance ranking between the two scenarios. Under both scenarios, the most influential parameter is f_{PAT}, followed by the maximum energy price difference $d_{Pel,max}$. Next are the two "soft" parameters $AT_{load,res}$ and l_{CRM}. Lastly, the feed-in tariff P_{FIT} and standard grid tariff $P_{grid,ST}$ are of intermediate importance, while the remaining parameters have little influence.

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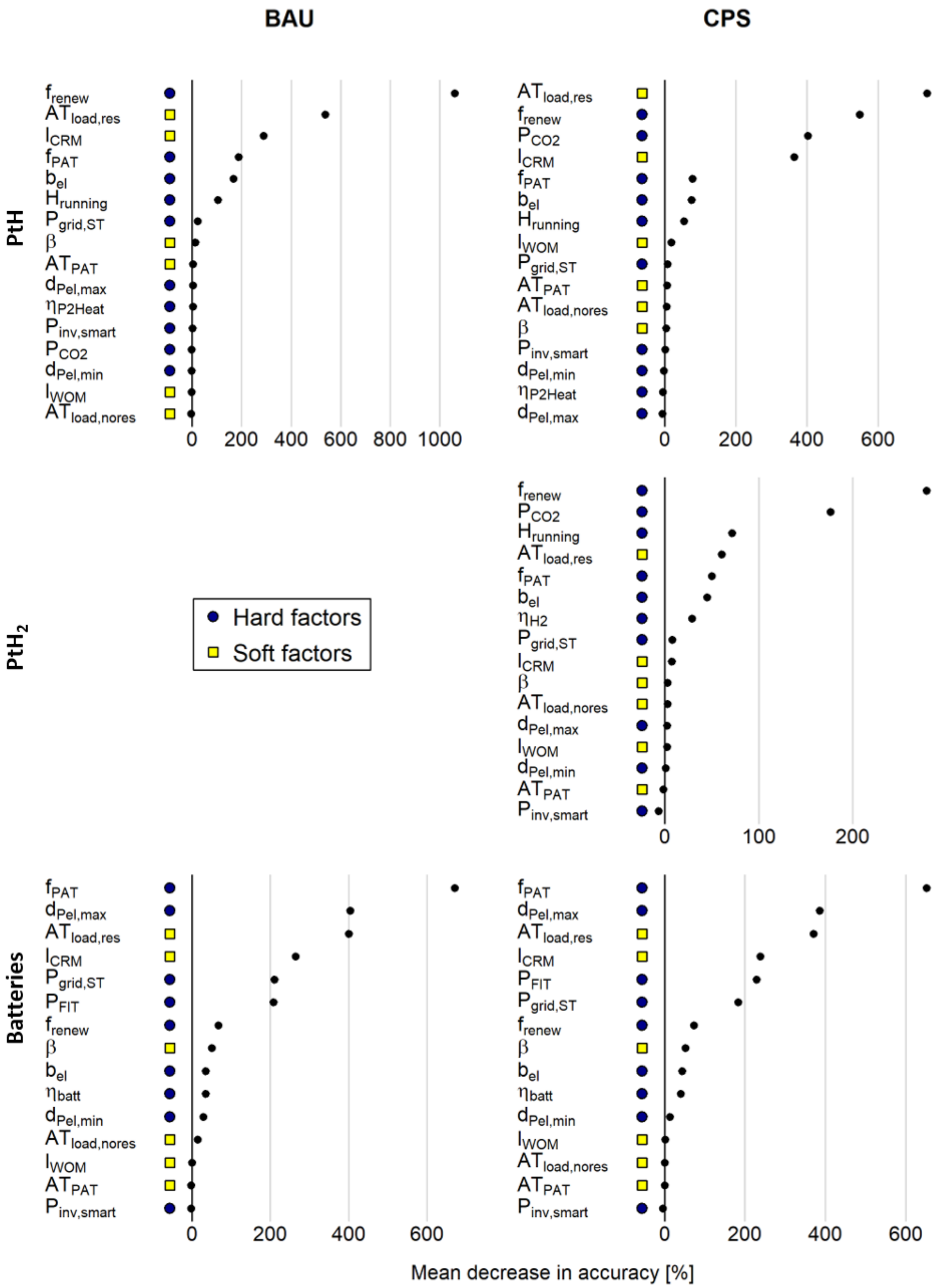

Figure 11: Parameter importance scores obtained in the sensitivity analysis. The score shown is the "Mean decrease in accuracy" indicator of the random forest meta-models. The higher the score, the more influence a parameter has on model outputs.

4.3. Roadmap

During the development of the project, we identified the most important barriers for the successful diffusion of flexible electrification technologies and the adoption of the proposed business model. Furthermore, through experimentation, we recognized the most important actions points needed to overcome these barriers. These insights were derived from the interpretation of the results, which is expanded on in the next section. With this information, we developed a roadmap (Figure 12) that coordinates the future action points among different actors (regulatory authorities, DSO, technology providers and utilities).

The role of the regulatory authorities is twofold: to provide the necessary grid conditions to allow the implementation of time-based business models, and to enact a CO_2-oriented reform of taxes, charges and levies on the different energy carriers. DSOs are called to offer new products that incentivize the customers to offer flexibilities, whereas technology providers and utilities should offer new complementary business models for flexibilities.

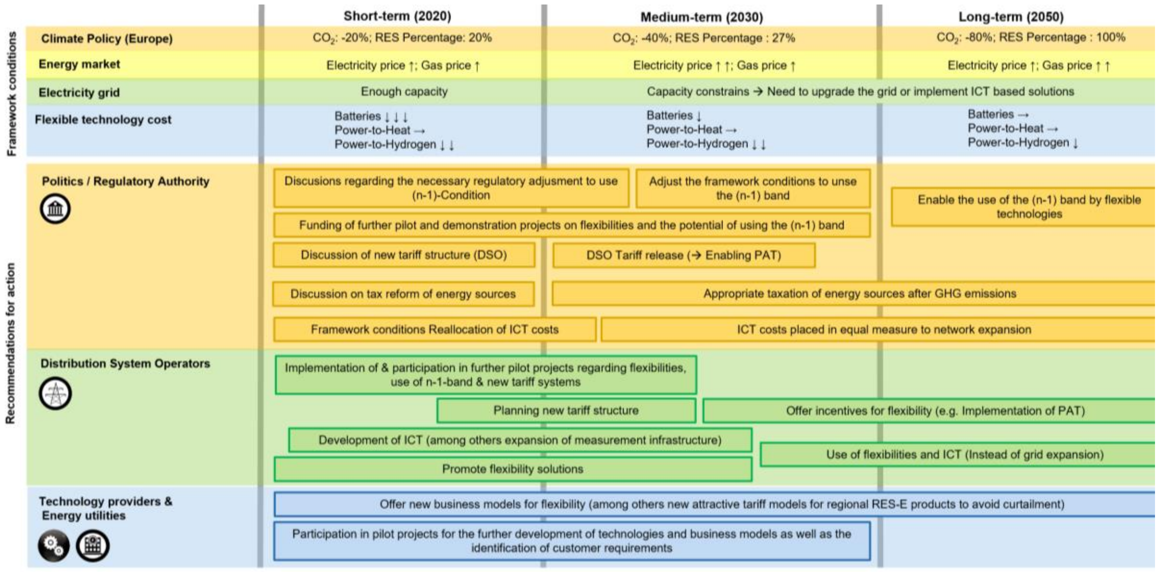

Figure 12: Roadmap for the implementation of the Power Alliance business model

5. Discussion

5.1. Methodical Approach

This paper developed a methodical framework consisting of the tailored integration of forecasting methods for business model innovation as a cost-efficient approach for experimentation under high uncertainty. Uncertainty in this case stems from two main sources: the potential for vastly different but equally plausible future economic and regulatory conditions, and a lack of empirical data for model building and parameterization. In this study, system dynamics, exploratory modeling and technology roadmapping were used for the design and analysis of a novel business model in the uncertain environment of the energy transition. With this integration, we profit from the strengths of each approach while at the same time minimizing their intrinsic disadvantages (see Sect. 2). First, we used the principles of BMI to identify and define new business opportunities for a DSO in the changing energy environment. In a series of workshops, we defined the characteristics of the new business model. The business model canvas (Figure 3) proved to be a useful tool to facilitate the discussion among the participants. For the experimentation phase, a SD model was set up to evaluate future market development and the prospects of the proposed business model under various future

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economic and regulatory settings. The model building process consists of mapping and operationalizing causal relationships between environmental factors, economic viability of flexibility technologies and customers' willingness to invest in them. This process yielded insight into market dynamics, as information was elicited from different actor groups. As the proposed business model was based on technologies that are currently rarely implemented and not well known by the target customers, there was only a limited empirical basis to build a model of the system and select values for parameters. Instead, the simulation model was constructed using well-known concepts from the literature on technological change, such as familiarity and scarcity effects. Under these conditions, a careful assessment of the uncertainties (see below) and limitations (see Sect. 5.3.) of the model was necessary.

Making the various sources of uncertainty explicit and quantifying their effect through computational experiments is a way to gain insight from a simulation model under high uncertainty [23]. In this study, sensitivity analysis had two functions: estimating the uncertainty of model outputs arising from uncertain parameter values and identifying potential levers of action and sources of uncertainty for the implementation of the business model considered. Both types of uncertainty contributed to the large spread of model results shown on Figure 10. The former function is especially important when no historical data is available for model calibration, as in this case. The parameters categorized as "soft" on Figure 11 refer to factors that are difficult to quantify in reality. They serve as proxy to integrate various economic, societal and human factors in the model structure. Two "soft" parameters were highly influential: the adjustment time strongly influences the adoption of flexible technologies and customer relationship management has a great effect on familiarity. As discussed in Section 3.2.3, a range of values was obtained from previous studies, where similar process formulations were used, but as these studies were carried out in different context, their values could not be directly transferred. Hence, the range for these parameters had to be kept broad, contributing to the spread of model results. Two other intrinsically uncertain parameters are the annual increase of energy price and maximum energy price difference, which is a measure of energy price volatility. The choice of a value for these parameters reflects an assumption on the future development of the power market.

While the sensitivity analysis assesses the uncertainty of model outputs due to parametric uncertainty, it does not account for other sources of uncertainty, due e.g. to uncertainty in time-varying inputs (e.g. technology prices) and in the model formulation itself [69], [70]. For a simulation study to be useful, it is crucial to address these sources of uncertainty [71]. In this study, this was done by involving actors in the model development process and eliciting parameter ranges and input values as well as causalities from experts. Also, the selected method allows the estimation of parameter importance at one point in time only (in this case, at the end of the simulation. Other methods for parameter importance assessment, e.g. calculating the correlation coefficient between parameter values and outputs, allow an examination of how parameter importance changes throughout the simulation [72]. On the other hand, the advantage of the random forest method applied here is that non-linear relationships between parameters and outputs, as well as interactions between parameters, are usually well captured by the statistical model.

In a last step, the insights of the whole process were summarized in a roadmap. This tool helped us translate the simulation insights into concrete recommendations and to present a coordinated action plan for different actors. The recommendations consist of concrete action points over time needed to reach the desired future.

While this paper focuses on a specific case in the energy sector, we expect that the method presented here can be transferred to other business contexts or sustainability transitions. Indeed, system dynamics was shown to be a valuable tool to conceptualize the process through which firms reconfigure their business models in the context of sustainability transitions [73], [74]. With its focus on (deep) uncertainty, the method applied here can complement these approaches to address the research gap on implementation and challenges of new business models (see e.g. Geissdoerfer et al., 2018) [75].

5.2. Implications for Policy, Strategy and Research

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Under current regulatory conditions, where electricity is strongly charged with taxes and levies, the diffusion of Power-to-Heat and Power-to-Hydrogen is very slow. This is consistent with previous findings [44], [57], [76]. Here, authorities have a high-leverage point to influence the adoption of flexible electrification technologies through a CO_2-oriented tax reform. Furthermore, the sensitivity analysis showed that one of the most influential parameters for the adoption of these technologies is the percentage of electricity consumption that can be covered by own RES. This suggests that the promotion of electrification technologies should go hand in hand with the support of local renewables. An additional measure would be to facilitate the use of local surplus renewables by reducing its cost and thus avoiding curtailment [77]. The relatively low sensitivity of model results to the annual energy price increase suggests that these measures would be effective regardless of the future energy price evolution.

There are important differences between technologies regarding the influence of environmental factors. For batteries, the simulated diffusion is almost independent of climate policy. Indeed, the use case selected here – increase of self-consumption combined with arbitrage – is already profitable under the current regulatory framework. Also, the diffusion of batteries is less sensitive to the fraction of own RES. On the other hand, energy price volatility and the level of a feed-in tariff are rather important determinants for the self-consumption savings, and thus for the profitability of the studied use case. The battery case also differs from the two other technologies through the importance of the per-capacity grid tariff and the reduction associated with the PA offer. These differences show that if a customer can choose between different flexibility technologies, their choice may depend on the specific configuration of their plant (e.g. the capacity to generate electricity from own sources) and their assumption regarding the future economic and regulatory environment. In the PA business model, one of the key activities of the DSO is to provide consultancy services to their customers. Further research on the internal and external factors influencing the comparative advantages of different technologies will be useful to define appropriate customer segments.

Finally, it is worth noting the high importance of some soft parameters of the simulation model. While hard parameters determine whether an investment decision is profitable, soft parameters determine how fast the diffusion process takes place. As discussed in Section 5.1, these parameters integrate various factors not explicitly accounted for in the model. For example, the adjustment times represent system inertia, i.e. the factors that keep customers from adopting a technology even after it becomes economically viable. Some of these factors are related to the perceived utility of flexibility technologies and load management by customers [47], [48]. As the objectives of authorities (meeting their GHG emission reduction targets) and DSOs (keeping the grid ready to deal with a higher share of intermittent renewables) are highly dependent on timing, it is crucial to address these barriers to technology diffusion. Further research should examine the causes of these barriers and provide guidance for DSOs and utilities to offer products where customers' concerns are addressed.

5.3. Limitations of this Study

The simulation model was developed with the aim of understanding the drivers and barriers to the success of the proposed business model and assessing the influence of uncertain parameters and future conditions. Model structure was deliberately kept simple to facilitate participatory modeling and computational experiments, following the recommendations of Bankes (1993) [34] and Ghaffarzadegan et al. (2011) [36]. Tractability and ease of handling come at the expense of completeness and precision. Therefore, the model cannot be expected to produce realistic forecasts of market dynamics under technological change, and the results from this study should not be understood as such. For example, the assumption that all customers are identical and can choose only one flexibility technology is clearly unrealistic. Rather, the simulation model forms the basis for computational experiments, where the outcome is the identification of drivers, barriers, leverage points and main sources of uncertainty. For the same reason, the two scenarios defined in this study are not meant to be complete and fully consistent, but to provide plausible boundary conditions for two possible future regulatory environments.

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The use cases studied here only represent a small subset of the possible use cases for flexibility technologies. They were selected based on the specific needs of the industrial partners who participated in the workshops. For example, flexible loads may participate in balancing energy markets to generate revenue, or the hydrogen obtained via electrolysis may be used as an energy carrier. Also, for each use case, the technical specifications (e.g. installed capacity) were treated as a given. With different use cases and specifications, the study might have reached different conclusions regarding the diffusion of different technologies. In addition, the proposed methodical framework needs to be tested and probably advanced in other business model innovations settings under high uncertainty in order to prove its value for practical application.

6. Conclusions

This paper presents a tailored methodical framework to assess the prospects of innovative business models under high uncertainty, applied to a case study in the energy sector. Business model innovation methods were used to identify new opportunities for a grid operator in the context of socio-technical transition to a low-carbon system; system dynamics and exploratory modeling approaches were used to assess under which conditions the proposed business model is promising; and technology roadmapping was used to visualize insights and provide recommendations for coordinated action to different actor groups. The proposed business model aims at reducing the need for grid expansion as the penetration of intermittent energy sources increases, by centralizing the management of some industrial appliances that have a certain degree of flexibility. In return, customers who choose to participate get a preferential grid tariff. A system dynamic model was built to simulate the diffusion of three flexible electrification technologies, upon which the success of the proposed business model depends. Analyzing the model with varying parameter values and boundary conditions yielded insights into the sensitivity of modeled diffusion to various economic, regulatory and soft factors. These insights were translated into concrete recommendations and visualized in a roadmap. This tool helped to orchestrate recommendations of actions among different actors.

Based on study results, concrete recommendations were formulated for coordinated action to create the conditions necessary for the success of the proposed business model. This study highlighted the role of energy costs as one of the main barriers for the adoption of flexible electrification technologies, as wholesale electricity prices are not cost-competitive with fossil fuels under current regulatory conditions. Policymakers have two important leverage points to overcome this barrier: implementing a tax reform on energy carriers by including an appropriate price for GHG emissions, and increasing the use of renewable generation facilities at local scale through measures to reduce curtailment. For distribution system operators, an important insight is that under a more stringent climate policy, the diffusion of electrification technologies will likely be faster. This means that new electric loads will be attached to the grid. To reduce grid expansion costs, DSOs should be prepared to offer new incentives to promote flexibility services, such as in the proposed business model. Also, this study highlighted the importance of customers' perception of the benefits and risks of new technologies, as a lack of information or a negative perception can greatly slow down the diffusion of these technologies even if they are profitable. Therefore, it is crucial for DSOs to know customers' concerns regarding electrification technologies and load management and ensure that they are addressed by the offered products. Finally, utility companies and technology developers should start offering new complementary business model to ensure the profitability of flexible electrification technologies and to reduce their dependency on external factors.

The purpose of combining business model innovation, system dynamics and exploratory modeling is to understand under which circumstances a proposed business model is promising, to identify what coordinated action should be taken to create favorable conditions for a business model, and to find out where more information and knowledge are most urgently needed. A strength of this method is that it enables business model experimentation at low cost, explicitly accounting for uncertainty regarding market dynamics and future economic and regulatory conditions. Where there is little empirical basis for model building, insights from previous studies and theory on technological

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change can be leveraged to represent processes in a plausible way. We suggest applying this approach in further business model innovation contexts and to improve the interplay between business model innovation, system dynamics and technological roadmapping.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Sections S1: Definition of use cases for flexible electrification technologies; S2: Utility functions in the system dynamic model; S3: Scenario definition .

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