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Development Of Data-based Business Models To Incentivise Sustainability In Industrial Production

Felix Hoffmann[1], Tobias Koch[1], Markus Weber[1], Matthias Weigold[1], Joachim Metternich[1]
[1]*TU Darmstadt, Institute of Production Managaement, Technology and Machine Tools (PTW), Darmstadt, Germany*

Abstract

Recent environmental catastrophes highlight the need to curb global climate change. Carbon dioxide (CO_{2e}) is responsible for the majority of the anthropogenic greenhouse effect. Politicians and society already exerted pressure for some time on industry and companies as major emitters. Despite continuously decreasing emissions, the savings achieved in the industrial sector fall short of the politically set targets. This is mainly due to the fact, that the combination of economic and ecological interests for companies is not promoted sufficiently. As a result, there is a lack of incentives for production companies to reduce their emissions. By incorporating economic aspects, data-based business models can create such incentives and thus support current and future regulatory measures.

This paper presents an approach of developing data-based business models to incentivise sustainability in industrial manufacturing. For this purpose, existing and potential future incentive mechanisms for the reduction of CO_{2e} are first identified and discussed. Subsequently, the business model approach for "CO_{2e} reduction in product creation" from the Gaia-X lighthouse project EuProGigant is presented. Finally, this approach is discussed in consideration of possible emission savings and the compatibility of economical and ecological company interests.

Keywords

Business Models; Sustainability; Digitalization; Data Analysis, GAIA-X

1. Introduction

The anthropogenic climate change and the resulting global warming cause a multitude of problems for humans and the environment. This becomes evident not only in the recent increase in extreme weather events, which have led to considerable economic damage around the globe [1]. Estimates suggest that the global economy will lose up to 18% of its GDP in 2050 due to climate change if no countermeasures will be taken [2]. For this reason, politics and society have already been working for decades to slow down or stop global climate change. Policymakers have set ambitious climate targets with the adoption of the Paris Climate Agreement [3] and the implementation of the European Green Deal [4] at European level. The reduction of climate-damaging greenhouse gas emissions is a key lever in this context. Along with increasingly strict regulatory measures, the pressure on companies to systematically reduce their emissions thus continues to grow.

For companies, though, switching to more sustainable production poses a number of problems and risks, as they primarily operate in a profit-oriented manner [5]. However, switching to sustainable production can mean a high level of effort and investment in new technologies and equipment. Such a changeover and

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investment must therefore be justifiable in terms of measurable benefits and return on investment. If competitors do not act similarly, they could achieve decisive advantages in the market through e.g. lower costs and thus displace more sustainable players [6]. In this context, data-driven business models can provide a way of unlocking additional potential benefits for companies that operate sustainably. By creating additional savings and revenue potential, they create incentives for manufacturing companies to reduce their emissions within current and future regulatory measures. Thus, the combination of economic and ecological interests of the companies is promoted [7].

Research on data-based sustainable business models in industrial production and the accompanying empowerment of companies is still in its infancy [8]. This includes both a structured and systematic approach to developing appropriate business cases and the practical demonstration of the potential in industrial use cases. In addition, there is a lack of approaches on how to enable the value creation mechanisms in these business cases to convert the additional value created into revenue [9]. The following remarks highlight future possibilities of data-based sustainable business models in production. First, the concept of a sustainable, data-based business model and current and future regulatory measures are discussed. Then, a possible approach for the structured development of corresponding business models in the context of Gaia-X is presented. Subsequently, the business model approach for "CO_{2e} reduction in product creation" from the Gaia-X lighthouse project EuProGigant is presented. Finally, this approach is discussed with regard to possible emission savings and economic potentials.

2. Related Work

2.1 Data-based sustainable business models

A business model captures the generated value proposition of a service offering and produces profitable outcomes through the application of a particular technology. In doing so, it represents a link between a technology and its economic value. It consists of the three complementary dimensions of value generation, value proposition and revenue structure [10]. The value proposition dimension represents the benefits that a company provides to its customers with a particular product or service. The value generation dimension captures the required key processes and competencies to fulfill the value proposition. Finally, the revenue structure dimension describes the composition of cost and revenue mechanisms. It thus determines the value generated from the business [11]. Data-driven, digital business models represent a special form and distinguish by their customer-centric, service-oriented value creation based on data and a fully digitized implementation [12]. In value creation, a data value chain significantly shapes the interactions in the ecosystem of such a business model [13]. The data used in this way is obtainable from various internal and external data sources [14]. In manufacturing, data often roots from the use of machinery and equipment. This is not least due to the ongoing transition from physical products to product-service systems and software-as-a-service models. Thus, the importance of dematerialized values is continuously increasing [15].

According to the United Nations Brundtland Commission, sustainability is defined as “meeting the needs of the present without compromising the ability of future generations to meet their own needs” [16]. Sustainable business models thus do not primarily aim for economic success, but complement an ecological and social target dimension. The resulting service offerings must therefore also contribute to an improvement in social and ecological performance indicators in the company and in society [8]. This creates an additional field of tension for the operating companies. The company's own positioning in the target system is largely determined by maintaining its competitiveness in the market [17]. In the context of Industrie 4.0, sustainable data-based business models can make a significant contribution to uniting economic and ecological interests. At research level, and to a lesser extent at industry level, technical approaches already exist to increase sustainability in production by leveraging data. These extend across different areas of the value chain [7]. By using data in maintenance, for example, it is possible to extend the useful life of machines and systems and their components. This enables to avoid emissions from the production of unnecessarily installed spare parts and non-optimal use of energy and resources as a result of wear-related degradation [18,19]. In the field of quality management, data-based applications are used for the early detection of production defects. As a result, emissions can be avoided by using energy and resources in the further processing of defective components and the destruction or costly recycling of scrap parts [20,21]. Finally, data is also used to optimize processes in terms of their demand for energy and resources and thus to make them more sustainable. In this context, operators are supported in the parameterization of the machines in order to generate an operationally optimal state [22].

2.2 Regulatory mechanisms

In recent years, an increasing number of regulatory measures were introduced in order to emphasize the demands of the climate protection agreements and to curb industrial emissions of greenhouse gases. These laws and regulations intend to provide companies with incentives to switch to sustainable technologies of their own accord and in accordance with market principles. They thus have a direct influence on the viability of sustainable business models. In addition to bans and verification requirements, incentives can also be subsidies or advantages, e.g. in taxation. The EU Commission is currently planning to introduce a digital product passport as an instrument for recording sustainability data along the entire product life cycle [23]. A possible tool in this context is the introduction of a CO_{2e} price, in which the emission of greenhouse gases is financially sanctioned [24].

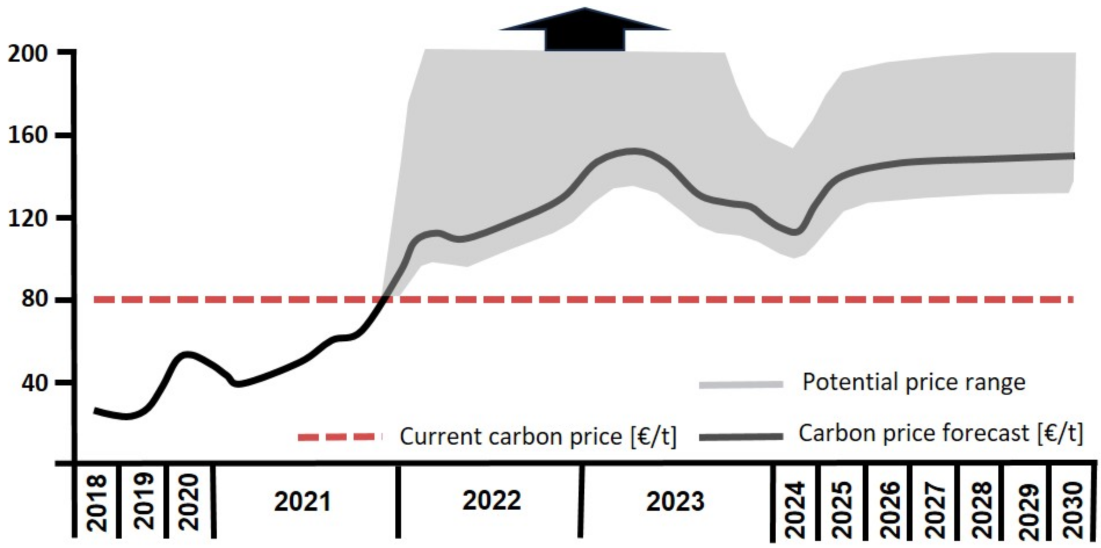

Figure 1: Price development for carbon emission certificates as forecast by [26]

The principle behind the CO_{2e} price are as follows: The emission of CO_{2e} causes damage to society in the long term. If the pricing of emitted CO_{2e} matches the amount of damage, an equilibrium is reached. At the same time, the incentive to emit CO_{2e} will decrease as the price of CO_{2e} increases. This financially sanctions every emitted amount of CO_{2e} and indirectly rewards every saved amount. One possibility is a simple CO_{2e} tax, where every emitted amount is taxed directly and with a fixed price. This creates a direct economic incentive to save CO_{2e}. An alternative concept is trading with so-called emission certificates. Here, the total amount of CO_{2e} that may be emitted at the reference level over a period is first determined. At the beginning of a commitment period, participants are allocated a number of emission certificates equal to their permitted emissions. At the end of the commitment period, emitters must demonstrate that their actual emissions do not exceed the number of emission allowances. Surplus allowances can be sold or stored, and missing allowances can be purchased from other participants. In Germany, a CO_{2e} tax or trading in emission certificates already exists for some industries through the European Union Emissions Trading System (EU ETS). This includes power generation, iron and steel production, glass, ceramics, paper and cellulose production, refineries and other subsectors of the chemical industry. Accordingly, there is no overall certificate trading system for the entire manufacturing industry, resulting in only indirect impacts in broad areas. In recent years however, the trading system has been steadily extended to other sectors [25]. Figure 1 shows the development of the EU ETS carbon price. It shows that the price has roughly tripled in the last 3 years and is expected to double further in the near future until 2023 [26]. In the future, a "Carbon Boarder Adjustment Mechanism" is intended to prevent CO2e emissions from being shifted on balance to countries outside the EU, which are monitored less strictly. This means, for example, that the location and energy mix of raw material production must be taken into account. In this course, it is then no longer permissible to calculate an average CO2e value for raw material supply. The emission content of raw materials will thus play a stronger role [23].

Pressure on the manufacturing industry is also increasing outside of legislative regulatory measures. Many large OEMs increasingly require their downstream suppliers to report certain sustainability parameters and to comply with defined threshold values. The OEMs hope that increased transparency throughout the supply chain will enable them to identify processes with particularly high emissions and to take countermeasures. Manufacturers who do not comply with these requirements may run the risk of losing their status as a preferred supplier [27].

3. Methodology

The overall objective of the underlying sub-research project is to develop a prototypical use case for data-driven reduction of greenhouse gas emissions in industrial production. A sustainable business model is needed to commercialize the technical solution as a marketable application. The project itself integrates into the research project EUProGigant, which is one of the lighthouse projects of the European Gaia-X initiative. Gaia-X aims to create an innovative data infrastructure based on European values. Thus, it also focuses on the aspect of sustainability. In their paper, Hoffmann et al. propose a funnel-shaped, iterative process for the development of data-based business models in the context of Gaia-X (see Figure 2) [28]. In this process, a problem is transformed into a commercially viable and executable application through the three phases of problem selection, solution design, and solution development. In the next chapter, the functionality and development of the business model based on the described approach will be explained in detail. A special focus is placed on the solution development phase. Subsequently, the economic and ecological potentials of the business model approach will be discussed.

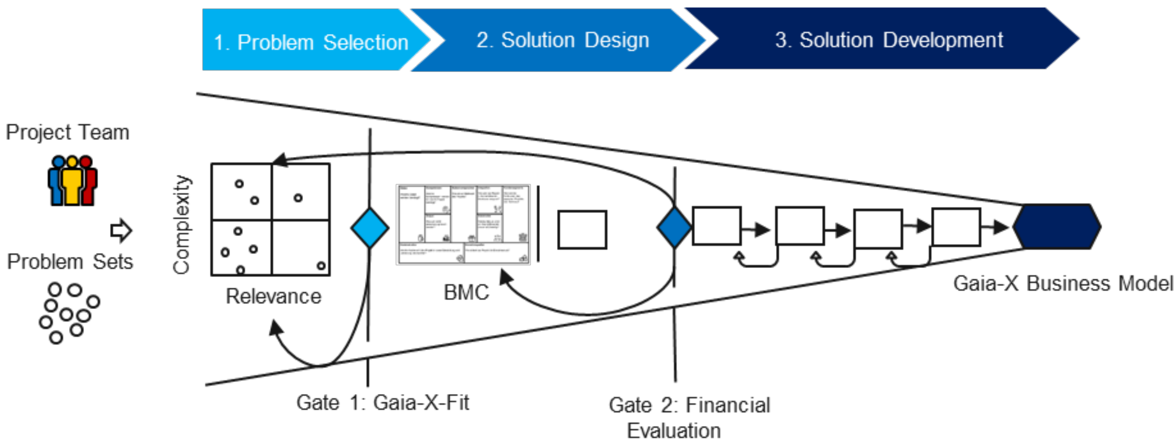

Figure 2: Development process of data-based business models according to [28]

4. Application

This section presents the current work on the "CO_{2e} footprint in product creation" use case within the EuProGigant project [29]. Due to the status of the project and the limited scope of the paper, the application is focused on the area of solution design. For this purpose, the use case is first described, and then the business architecture is depicted. The results presented were developed within interdisciplinary workshops with project participants. Domain experts from the fields of polymer processing, data scientists, as well as software developers were among the participants.

As illustrated in section 2.1, a number of different approaches to improve sustainability in production by leveraging data already exist. However, these approaches mostly focus on the product manufacturing phase. In order to develop innovative sustainable business model approaches, it is thus necessary to have fundamental transparency over the entire product life cycle. According to a recent study by Fuchs et al., „up to four-fifths of a product's lifetime emissions are determined by decisions made at the design stage" [30]. If these potentials are only identified in later phases, their implementation may involve considerable and, in the worst case, unrealizable effort. For this reason, the effects of subsequent phases should be implied as early as possible in the product design phase or as early as possible in the product development process. A clever design can then reduce CO_{2e} emissions without limiting the actual functionality of the product.

In the production of components in the mechanical engineering sector, there are various levers for influencing lifecycle CO_{2e} emissions [31]. In the present application, these were identified by experts specifically for the area of plastics processing. The first lever identified is the selection of materials for the product. It becomes apparent that materials with similar properties require significantly different CO_{2e} footprints for their production. This effect is reinforced by the increasing spread of organic-based polymers designed for particularly low emissions [32]. It is also evident that different polymers have different processing properties. The temperatures required to melt plastics and the injection pressure needed to form them differ significantly from one another. This impacts not least on the energy required to carry out the manufacturing process and thus on CO_{2e} emissions. The emissions generated during transport and the energy and resources required for recycling are further influencing factors. Another lever is the selection of the underlying manufacturing process. In the industrial context, injection molding, machining and additive manufacturing are the predominant processes used to manufacture functional components from thermoplastics [33]. Each process brings different specific properties that affect CO_{2e} emissions. In the case of machining, a key factor is that components are mostly machined from the solid. This results in a relatively high volume of machined material, which in turn has to be recycled or destroyed [34]. With injection molding, this process-related waste is much less pronounced. On the other hand, a high level of energy and material input is required for the production of the injection mold itself [35]. Depending on the exact process, there is no waste in additive manufacturing. However, due to the significantly longer processing times, the manufacturing of a single component is much more energy-intensive. Within manufacturing processes, there

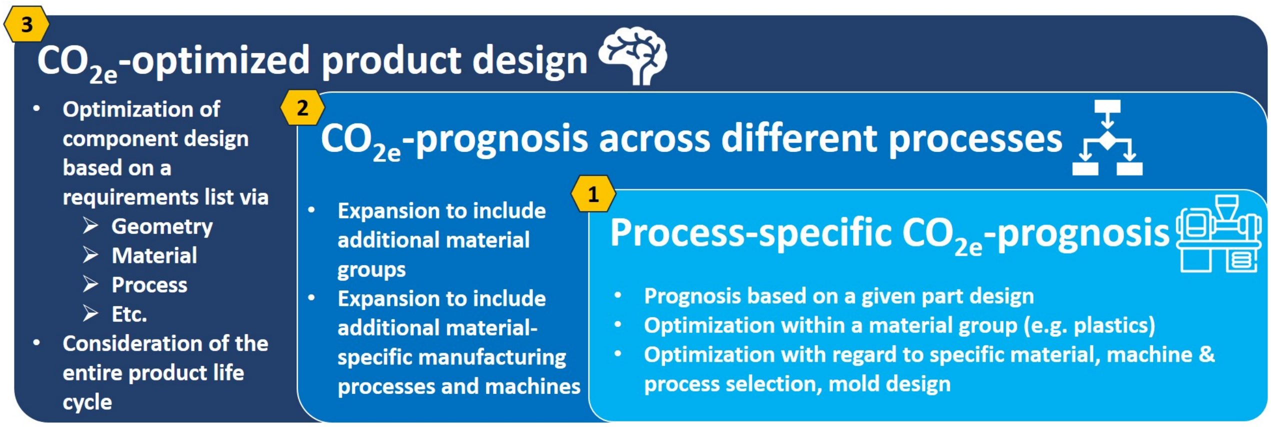

Figure 3: Development stages of the business model "CO_{2e} footprint reduction in product creation"

are again further opportunities to influence lifecycle CO_{2e} emissions. Here, the injection molding process acts as an example: It often happens that machines are over-dimensioned, which increases the energy consumption to carry out the process. The design of the mold determines the number of components that can be produced in one shot and simultaneously the volume to be heated.

Industrial practice shows that optimization efforts often fail because there is no exchange between the relevant actors. In order to exploit the emission saving potentials identified, EUProGigant develops an approach for optimizing the "CO_{2e} footprint in product creation". The concept builds on the Gaia-X data infrastructure, which conforms to European values. It aims to promote exchange between the relevant players in product creation to minimize CO_2 emissions. Figure 3 shows different expansion stages of the business model approach in relation to the value proposition. In the first stage, an existing component design is optimized - e.g. with regard to material and machine selection - within a certain type of manufacturing process. In the second stage, the value proposition includes a comparison of different types of manufacturing processes. The third and final stage finally enables to generate a CO_{2e} optimized product design based on a requirements list.

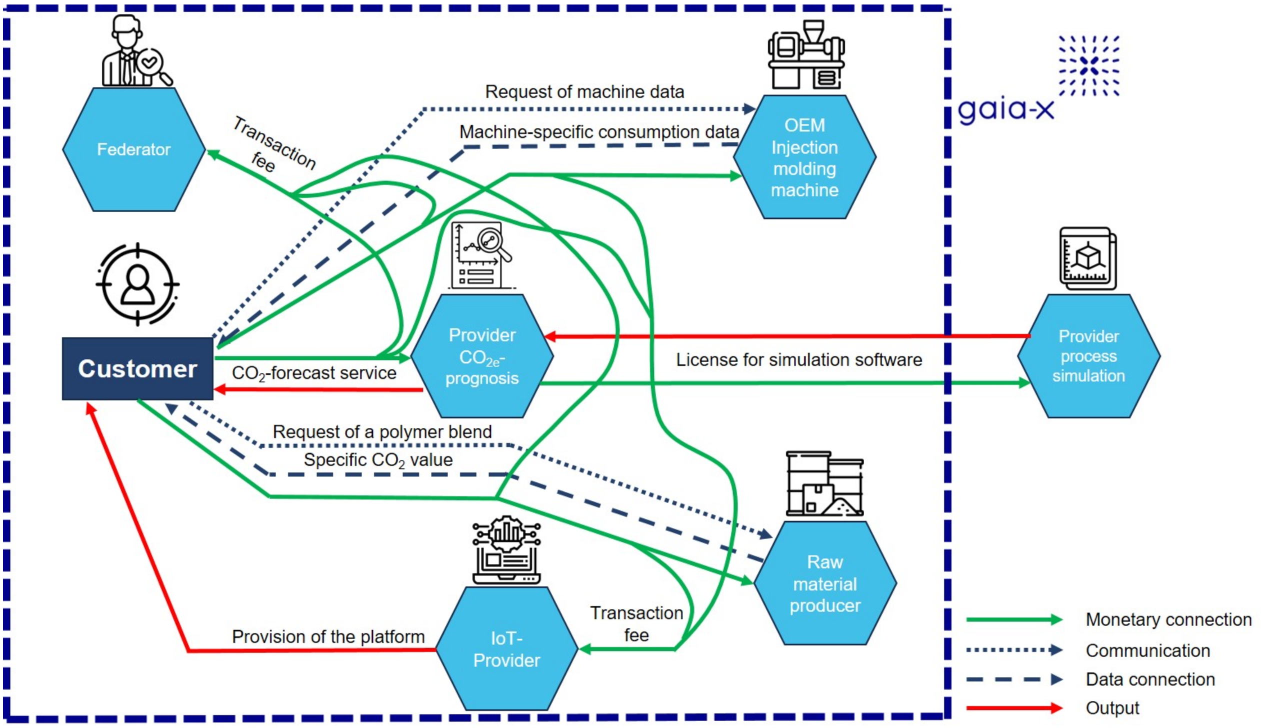

Figure 4: Business model architecture of the "CO_{2e} footprint prognosis in product creation"

Figure 4 shows the developed business model architecture of the first stage with the representation method according to Kölsch et al. [36]. It shows the players involved within the business model and their relationships to each other for the case of plastic injection molding. The key players in the business model are injection molding machine manufacturers, raw material producers, process simulation providers, IoT providers, a Federator, the customer, and finally the CO_{2e} prognosis service provider himself. The relations divide into data connections, communication, monetary connections, and outputs. The OEM and the raw material supplier provide data to the customer and are financially compensated by him. In the case of an OEM, this is precise data on the energy and operating material consumption of its machines, and in the case of the raw material manufacturer, information on the CO_{2e} footprint and the processing properties of its materials. The provider of the CO_{2e} prognosis provides the customer with its digital service for processing his component data and the purchased data for a charge. To enrich its service, the CO_{2e} prediction provider uses simulation software from the process simulation provider. Here, it is also conceivable that the simulation provider itself is simultaneously the provider of the CO_{2e} prognosis. The IoT provider offers its platform for interaction between the aforementioned players. He charges a transaction-based fee for this. The same applies to the so-called Federator. The federator verifies that all parties involved are compliant with the Gaia-X standard and that only approved parties exchange data.

5. Discussion

The procedure was adapted to an exemplary use case in order to analyze the effectiveness of the business model. A holding bracket was selected as an example component, which is manufactured by one of the application companies within the EUProGigant project. Table 1 shows the comparison of different materials, manufacturing processes and machine concepts for one bracket. With all combinations mentioned, the component produced meets its functional requirements. In the initial state, the component is manufactured from polyamide on a hydraulic injection molding machine. This serves as a baseline for the calculated relative emission savings.

Table 1: Evaluation of the effects of a CO_{2e}-optimization in product creation

Machine	Material	Emissions/ part [%]	Share of Energy [%]	Share of Material [%]	Energy cost* [€]	Emissions cost** [€]
HIM	PA	100	16	84,0	0,0024	0,0096
HIM	PP	25,1	4,4	95,6	0,0022	0,0024
EIM	PA	76,9	12,8	87,2	0,0023	0,0074
EIM	PP	18,2	4,4	95,6	0,0019	0,0017
3D-Printer	PA	1897,2	99,2	0,8	1,0349	0,1827
3D-Printer	PP	517,4	85,8	14,2	0,2442	0,4983
HIM = hydraulic injection molding				EIM = electronic injection molding		
*considering an energy price of 0,35€/kWh						
**considering an emission price of 150€/tCO_{2e}						

The evaluation shows that by applying the proposed solution in the present case, considerable potentials for saving greenhouse gas emissions can be realized. A changeover from PA to PP, for example, already leads to a reduction of around 75% when using the existing machine. By switching to a modern electrically driven injection molding machine, another 7% of emissions can be saved compared to the initial state. Broken down to a single component, the use of a 3D printer leads to drastically higher emissions than injection molding. However, this does not take into account that for the injection molding process, significantly more emissions are caused during the production of the mold. From an economic point of view, potential improvements can also be expected. The changeover from PA to PP while using the existing machine results in a reduction of energy costs by approx. 10%. An additional conversion to the electric injection molding machine saves a total of 20% of the energy costs. Despite the relatively small amounts of energy costs in absolute terms for the production of a component, this can lead to significant savings in the company if a very large number of produced units is taken into account.

As already explained in chapter 2.2, politically initiated regulatory measures can lead to a significant change in the viability of sustainable business models. For this reason, the evaluation also considered the hypothetical scenario of introducing a CO_{2e} price for discrete component manufacturing. The price of 150€/tCO_{2e} predicted by [26] was assumed here. Based on the greenhouse gases emitted in the machining process of a component, this leads to additional costs as much as four times the energy costs of the initial scenario. In the optimum scenario with PP on an electric injection molding machine, these costs can be reduced by approx. 80%.

6. Conclusion and Future Research

This paper presents an approach for developing sustainable data-based business models in the context of industrial production. First, the necessity of such approaches was motivated and the fundamentals were described. In this course, the profound influence of regulatory measures on the viability of business models was revealed. Finally, an exemplary business model was developed using an existing method. Its potential in terms of profitability and sustainability was finally evaluated by applying it to a practical use case. It was shown that the solution presented in the considered case achieves significant savings in terms of greenhouse gas emissions and energy costs. In addition to these cost savings, companies can thus also be supported in complying with the limits imposed by legislators or customers. In the case of an extension of CO_{2e} pricing to the sector of discrete production of machine components, this effect would be significantly enhanced.

In the current state of development, some simplifying measures have been adopted, allowing opportunities for future research in this context. The consideration of quantity-related effects offers a point for further elaboration. This includes e.g. the impact of emissions due to the production of tools or repair measures. Furthermore, great potential is expected by extending the method to other materials and manufacturing processes. This represents a fundamental prerequisite for ultimately enabling sustainability-optimized product design based on component requirements.

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Biography

Felix Hoffmann, M. Sc. is a research assistant and PhD student at the Institute of Production Management, Technology and Machine Tools (PTW) at the Darmstadt University of Technology since 2019. His research interests are ML-driven Business Models in manufacturing and Predictive Maintenance. Since 2022 Mr. Hoffmann is head of research at the Production Management department of PTW.

Tobias Koch, M.Sc. is a research assistant and PhD student at the Institute of Production Management, Technology and Machine Tools (PTW) at the Darmstadt University of Technology since 2022. His research interest focuses on cyber-physical systems in climate-neutral production.

Markus Weber, M. Sc. is a research assistant and PhD student at the Institute of Production Management, Technology and Machine Tools (PTW) at the Darmstadt University of Technology since 2017. Mr. Weber was head of research at the Manufacturing Technology department of PTW from Jan. 2021 until May 2022 and he is project coordinator of EuProGigant.

Prof. Dr.-Ing. Matthias Weigold is the head of the Institute for Production Management, Technology and Machine Tools (PTW) at the Darmstadt University of Technology with responsibility of the manufacturing and energy efficiency research groups since 2019. Prof. Weigold contributes many years of industrial experience from management positions at Heidelberger Druckmaschinen AG and SAP SE.

Prof. Dr.-Ing. Joachim Metternich is the head of the Institute for Production Management, Technology and Machine Tools (PTW) at the Darmstadt University of Technology since 2012. In addition, Prof. Metternich is the spokesman for the Center of Excellence for Medium-Sized Businesses in Darmstadt and president of the International Association of Learning Factories.