# Planet 2050 and the Future of Manufacturing: Data-Driven Approaches to Sustainable Production in Large Vehicle Manufacturing Plants

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**ABSTRACT**

This paper explores the future of manufacturing plants in large vehicle manufacturing through the lens of a single large European vehicle manufacturing complex. An example of a plant that originally mass-manufactured a single line of products, the complex is currently navigating a shift to more complex mixed model production and the production of electric vehicle powertrains. Using innovative datasets generated through a year-long stakeholder co-design process, a diverse set of partners collectively formed a project to design new, data-driven approaches to the challenge. The project collected and explored diverse data sources, including product bills of materials, facility layout data, current manufacturing system capabilities, energy usage and carbon generation, machine uptime and failures, factory control strategies, planning processes, and product quality data. The paper provides a summary of the explored data, key analyses, feedback from the stakeholders, early technical project interpretations, as well as broader project reflections and contextual descriptions of the factory – particularly of its goals and current challenges. The project supported stakeholders in exploring the potential of digital approaches to transform and facilitate the current manufacturing system's CO2 reduction pathway. The paper concludes by outlining several thematic issues facing large vehicle manufacturing plants.

**Keywords:** Production change, data-driven approach, vehicle manufacturing, sustainable production, operational high-level control, semantic information, production system monitoring, large vehicle.

## 1. INTRODUCTION

There is already an abundance of literature focusing on production processes and their environments in large vehicle production factories such as steel mills, automotive plants, and shipyards. Many of these publications address material processing technologies, the design of processes, process scheduling, or operational planning derived from production plants. Yet, not only industrial companies, but also society as a whole, are calling for production to become more sustainable, and this should, as far as possible, influence how future large-scale production plants are designed. Given this demand and the high levels of CO2 emissions seen in large vehicle production plants, sustainability issues are becoming ever more important. However, the secondary or tertiary industrial sectors in which large vehicle production industries reside do differ in some respects, and any solutions emanating from the primary industrial sector are not necessarily directly transferable across the other industrial sectors.

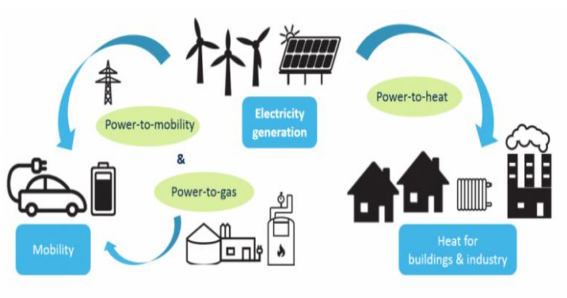


**Fig 1:** Sustainable transport

### 1.1. Background and Significance

The future of our planet is at stake due to rapid changes and degradation caused almost exclusively by humans. The conventional way manufacturing is undertaken today leads to significantly large numbers of products that are produced, used, and after a very short period of life, discarded. The trend, amplified by designed obsolescence, seeks to maximize profits by creating a short-term need, ensuring the repurchase of the products to sustain the manufacturing business due to decreasing customer demand for new products, leading to a shrinking customer base. Companies may meet the final aim of covering expenses and making profits during the five to ten years, which is the usual advertised life of these consumable products that are in high demand for short periods through spin-off business while receiving regular orders for the mini version to virtually ensure the survival of the main business. The policy-making emphasis on consumer rights should now upgrade to consumer knowledge and consumer responsibility, following the motto: implore the client to be more responsible, adding yet more value and usefulness to the preference before, during, and after the purchase. Climate change and the potential resulting increased international contact have played a part in this product demand and its follow-up life disruption.

### 1.2. Research Objectives

The primary objective of this research is to develop, validate, and advance the standards for future production systems. The pre-competitive problems that must be anticipated and solved will encompass the need for identification and development of the scientific and engineering processes underpinning sustainable mass production; demonstration of novel tools and technologies; and the specific needs for human behavior training, implementation tasks, obstacles, and evaluation of remediation activities. The combined challenges of the above will produce the evaluation of new concepts and methods to evaluate, improve, and determine critical processes that achieve and maintain sustainable production. Practical progress toward these aims requires demonstration of a programmatic approach. In turn, the latter requires the development of a Manufacturing Research Vision, achieved through a roadmap that encompasses reduced environmental impact design aspects, low environmental impact operation costs, superior end products, stabilization and growth of the workforce, and acceleration of technology transfer to industries. These manufacturing research trends have been identified and widely recognized in several forums.

**Equ 1: Collected according to the model**

$$\sum_i a_i^2 = \sum_i \left[ \frac{1}{n} - \frac{\bar{x}\left(b_i - \bar{b}\right)}{\sum_i \left(b_i - \bar{b}\right)\left(x_i - \bar{x}\right)} \right]^2$$
$$= \frac{1}{n} + \frac{\bar{x} \sum_i \left(b_i - \bar{b}\right)}{\left[\sum_i \left(b_i - \bar{b}\right)\left(x_i - \bar{x}\right)\right]^2}$$

## 2. Current Challenges in Large Vehicle Manufacturing Plants

Vehicle production is inherently a pollutive process, with large vehicle manufacturing plants having significant energy requirements. As measures are enacted to meet national and international commitments to sustainable development, the manufacturing sector will inevitably be impacted. Hence, these challenges must be managed. Research has shown that leveraging data for sustainability purposes can be achieved simply by employing data that already exists within the manufacturing plants. However, in utilizing data for sustainability purposes, privacy and security risks take on an additional dimension. This paper outlines challenges that are likely to occur as large vehicle manufacturing plants undergo transformation followed by new roles regarding the governance of sustainable data-driven manufacturing processes. This paper goes further to suggest various sustainable options that large vehicle manufacturing plants can employ to operate in an increasingly resource-restricted and energy-constrained environment.

Since the early 1900s, business practices and technological advancements have led to a continually increasing ability to mass produce quickly and at relatively low costs. Despite recent national and international commitments to meeting sustainable development goals and adopting environmental policies, large vehicle manufacturing plants and their operations management will be increasingly constrained by the impending resource availability and climate change. There will be considerable measurement and governance challenges that the Factory of the Future's operations management function has to face and evolve to address the bringing together of data for driving efficiency gains and improved environmental performance.

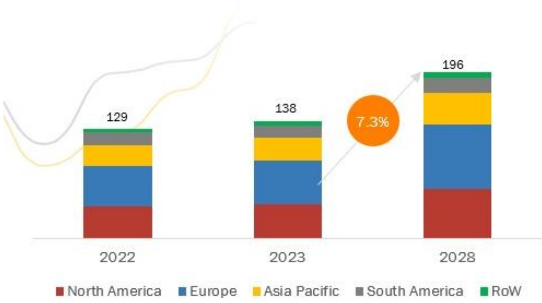


**Fig 2:** Plant Factory Market

### 2.1. Environmental Impact

Future large vehicle automotive plants are increasingly likely to be located in or near expanding cities, with the potential to place significant economic value and job opportunities alongside damaging externalities. These externalities include large local environmental footprints and the high congestion, commuting costs, and pollution-transporting impacts associated with loading logistical requirements onto the local communities and locations of these plants. Positive action previously required for long-term manufacturing locations in peripheral, isolated locations is thus even more essential in a 'smart' city world, both as a governance priority of the smart cities themselves and of the multiple value chains that connect these increasingly complex business entities to larger manufacturing plants. In compact, clean, mixed, and 'smart' cities, nearby large factories of different types can be charged with generating and storing also the non-knowledge-based forms of capital, creating a physical 'knowledge bridge' inequality that goes beyond human capital. With more large vehicle centers from other companies, the relatively benign ambient presence of a large vehicle plant could be re-meshed into a local innovation environment, freeing the plant from the need to mitigate the impacts daily – using space-based low-vibration manufacturing concepts and urban 'smart'-ness to create anti-vacuums in which creative human capital is not only retained but encouraged. Large-scale, high-trust local graduate sponsorships could further encourage creativity in serving society, reducing resultant levels of output and manufacturing pollution impact and allowing the concentration on vehicle and component assembly to be complemented by small-scale environmental health benefits for local community citizens.

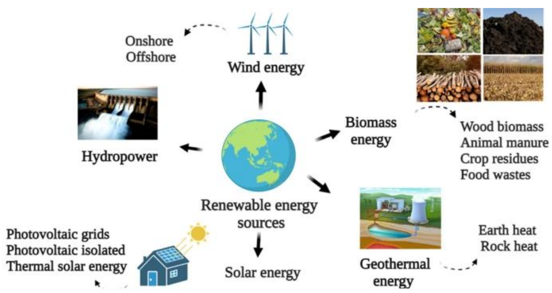


**Fig 3:** Environmental impact

### 2.2. Resource Management

Effective resource management can help to reduce energy consumption in the manufacturing environment. A significant obstacle to achieving effective resource management in large vehicle manufacturing plants is the availability of large amounts of diverse data and complex, dynamic decision-making. The concept of smart manufacturing in manufacturing environments often involves the formation of a real-time digital twin process, which is a virtual representation of a particular physical process that allows the real-time digital examination of the process and its operating conditions, as well as the real-time digital guidance of the actual process to achieve certain desired performance parameters.

To make the digital twin capable of real-time operation, the status of the physical and digital processes has to be interrogated and updated regularly via data acquisition from relevant sensors. A variety of data-driven approaches, such as signal processing, operational optimization, condition monitoring, and predictive modeling, have been developed to handle the large amount of heterogeneous manufacturing data generated in modern manufacturing plants. At the heart of these data-driven approaches is data analytics, which involves making sense of the data through exploratory data analysis, hypothesis testing, inferential statistics, machine learning, and signal processing.

## 3. Data-Driven Approaches in Manufacturing

At their core, data-driven approaches refer to the fact that decisions in an application of interest are motivated by a combination of modeled relationships as well as data capturing these relationships. As such, data-driven approaches estimate relationships in data, build models from relationships estimated in data, and finally use these models as decision support tools. In large vehicle manufacturing plants, data-driven approaches, essentially modeling things that produce data, will likely be used to facilitate various activities associated with achieving benefits that are expected and forecasted as likely to be achieved. These benefits can be classified as cost savings, improved quality, and increased responsiveness to market shifts, along with concomitant improvements in the use of resources.

Feasible data-driven approaches in large vehicle manufacturing plants involve a variety of predictive modeling techniques used tightly and/or in combination, to improve both "black box" and "systems understanding". Some such techniques of primary importance in manufacturing are presented below. Using these methods in large vehicle manufacturing plant operations will enable production system improvement efforts that can mitigate the adverse environmental effects along with improving economic performance. Such improvements provide good examples of activities that will enable manufacturing to enhance its attractiveness as a desirable occupation and contribute to the broader interests served by manufacturing prosperity in the context of "Planet 2050". The bonus of these improvements is an improved perception of the overall manufacturing system as both a desirable place to work and a desirable citizen of the distinct societal communities where operations are located.

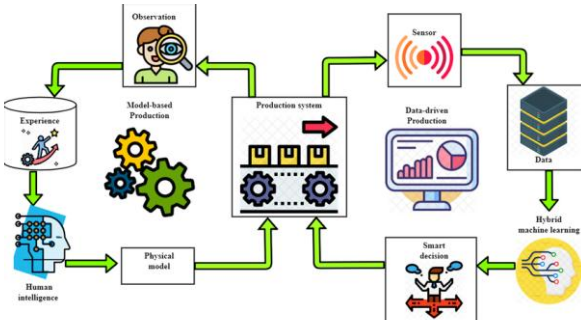


**Fig 4:** Data-driven and model-based production

### 3.1. Internet of Things (IoT) in Manufacturing

Leveraging the IoT in large vehicle manufacturing plants as part of the journey to a circular economy is a significant challenge. The sheer scale, material variety, and material handling involved in a large vehicle manufacturing plant require new architectures for data-driven decision-making. The large vehicle manufacturing benchmarking tool developed during this study can be adapted for the broad area of manufacturing operations, including the plants that assemble light vehicles and electric vehicle companies. The tool segments the asset-intensive operations of a large vehicle manufacturing plant and ensures that data-driven approaches can be deployed to help decision-makers in their quest for a highly efficient manufacturing plant. The future problems are understudied but substantial and can guide future circular economy initiatives in large vehicle manufacturing plants.

Large vehicle manufacturing plants consume a great deal of resources due to the high material intensity, energy consumed, and waste emitted during production. For large OEMs, the scale of activity in plants adds another layer of complexity to the challenge of identifying the factors that drive resource sustainability, circular economy performance, and robustness. While there is a breadth of IoT-related smart manufacturing literature, there are many challenges that the large vehicle manufacturing plant setting introduces, such as data privacy issues, the challenge of integrating multiple legacy systems that are not designed to work together and must be respected due to data governance, the scale, variety of materials handled, and complexity of the battery assembly area that supports electric vehicle production, and organizational silos that are very difficult to overcome.

**Equ 2: Negative binomial distribution**

$$p = \frac{1}{1+\beta}$$

$$\Pr(X = k) = \binom{k+r-1}{k}\left(\frac{\beta}{1+\beta}\right)^k\left(\frac{1}{1+\beta}\right)^r$$

$$\mathrm{E}(X) = r\beta$$

$$\mathrm{Var}(X) = r\beta(1+\beta).$$

### 3.2. Big Data Analytics

This is the step of the pyramid, the moment that the internal collection of data, both about the functioning of the factory and each of the units, as well as what the production generates, ends up producing dozens of terabytes that will be used for data-driven analysis supporting the global objectives for the full functioning of the factory to be designed at level one. Through this work, the necessity of aiming at the construction of these four steps in the factory of the future data pyramid becomes clear. To map data and decision-making within a large vehicle manufacturing plant, the relations between different data sources and models, connected with specific business goals to support production, and even routines to maintain green logistics and waste resources are used. At level zero of the pyramid, the focus of the research is to understand where this data is born, regardless of the location or systems of the factory, technological area, or production environment, like baking parameters of each furnace in the plant, each service event that happened to the production unit action-type transaction management system component, inputs from data on lean manufacturing, and measurement of logistics indicators.In the evolving landscape of the factory of the future, the initial phase of the data pyramid emphasizes the critical importance of data generation across various facets of production. At level zero, the focus is on identifying the origins of data—ranging from baking parameters of furnaces to service events within production units and inputs related to lean manufacturing practices. This comprehensive data collection, which can accumulate into terabytes, serves as the foundation for subsequent analytical processes. By mapping the intricate relationships between diverse data sources and their relevance to specific business objectives, manufacturers can enhance decision-making, optimize production workflows, and promote sustainable practices in logistics and resource management. This foundational step is essential for creating a robust framework that supports the full operational capabilities of advanced manufacturing systems.

## 4. Sustainable Production in Large Vehicle Manufacturing Plants

With the need for immediate action to help mitigate the potential impacts of climate change becoming clear, attention is turning to every facet of global industry and the need to deploy sustainable techniques. Many industries have already adopted circular economy policies in an attempt to change their business models away from harmful single-use consumption and disposal and refocus them on reusing waste materials and incorporating resources more effectively. Beyond material transformation, the question of what to do with waste heat is also driving attention. Increasing the energy efficiency of industry represents a global challenge for the transition towards sustainability. Data analytics enters the stage in all these areas and, as such, it is becoming a main subject of research in manufacturing circles in academia and industry alike. Modern factories are complex systems that create extraordinary amounts of data at every stage of production, and by incorporating the data to refine and optimize production, processes can be made to work as efficiently and sustainably as possible.

The question can be asked: what kind of assistance can data-driven techniques provide to support businesses in better-employing energy resources while supporting economic growth? Although these kinds of technological advances are mainly discussed about future factories, their potential applications are broad, including large vehicle manufacturing plants. What are the main areas where directed research effort has been invested? To name but a few, real-time energy consumption and forecast models to predict energy usage and autonomously optimize load balancing across the plant during variable operations and peak demand periods.

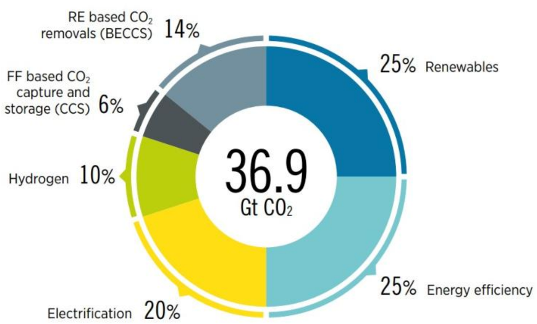


**Fig 5:** World Energy Transitions

### 4.1. Energy Efficiency

Identifying opportunities and developing strategies that improve the energy efficiency of large manufacturers, their products, and the extended supply chain not only has significant positive implications on cost but also has equally high positive effects on the natural environment. The natural environment will benefit from decreases in climate-changing gas emissions, decreases in industrial solid, liquid, and gas emissions of industrial pollutants, and reduction in the use of limited natural resources. This section focuses on energy efficiency improvements. Data acquisition, preprocessing, and tools development support many data analysis tasks related to energy consumption: maintaining smart meters and monitoring systems across all primary customer utility dimensions, as well as model-building frameworks, and addressing the scarcity of data specific to energy-related external suppliers. Additionally, opportunities for electricity, gas energy, and water conservation at the site level were defined to the detail of specific manufacturing and refining sources—for example, boilers, or the use of process fluids that can be heat-exchanged—ideas needed for the final emerging joint facility change recommendation. Opportunity areas are separated from plant-specific solutions based on potential inherent across all existing sites to improve the consistency of energy volumes to be managed within the owner's portfolio, and presented in business terms that plant equipment managers and other stakeholders can understand, utilize, justify, and implement. Implementing an appropriate sampling strategy and protocol cost-effectively answers the appropriate monitoring and verification approaches and informs how projects can measure optimization outcomes over time. Conserved energy use requires periodic calculations, and error bounds should be computed and compared over time to ensure that project energy conservation work delivers savings.


**Fig 6 :** Energy Efficiency

**4.2. Waste Reduction**

The economic sustainability of present industry systems or newly developed approaches will require a reduction in the material inputs that are specific to the manufacturing process. The mono-material principle applied to the supply chain should continue to minimize overall part weight increases in the future. Material savings and recycling must also be increased when developing a diverse material paradigm. It is necessary to reduce the "material lock-in" that happens when stakeholders with different roles do not collaborate, making recycling difficult. Since awareness of the end-of-life condition is fragmented across the life cycle, extended life cycle thinking may help foster the definition and addressing of the recycling needs in the initial phase. The increase in mono-material application makes it possible to separate waste already from the collection phase. With the higher level of automation installed, it is possible to carry out more selective disassembly. As far as integrated factory waste recycling is concerned, the main critical issues are related to the imbalance of the materials recycled, the clarity of the materials, and the provision of a stable and automated system to avoid the interruption of the collection process in the different phases necessary to ensure correct recycling. All of which should be managed in collaboration with external partners. The continuous design cycle aimed at monitoring the actual behavior of the recycled materials is a strategic factor to strengthen the impact of both the technical and economic environmental advantages.

## 5. Case Studies and Best Practices

This chapter has presented two case studies, one of a plant in Germany and the other in France. We detail the data sources as well as the methodology employed. The best practices revealed for each of the four sections of the framework are described. Then, a section of discussion is conveyed, where best practices are discussed, and the whole company's data-driven approach to sustainable production serves as an example of a real implementation of data-driven sustainable production in practice.

Two parts of the plant complex currently do not belong to the manufacturing network since the production of each site is progressively being terminated. Therefore, only manufacturing sites are utilized in this report. The descriptions and explanations detailed in this report are largely based solely on the perspective and history. Therefore, nominal vehicle volumes, resources, labor agreements, and other site-specific conditions have been published. In contrast to similar works, an industry solution prototype has been implemented, leveraging substantial data from the vehicles' final assembly and environmental and energy-related datasets. The work aimed to model energy and material consumption in the press, manufacturing, and final assembly subsets of the plant, analyze systemic and case-specific energy consumption patterns, and define possible strategies to increase plant sustainability and energy efficiency.

**Equ 3: Nernst equation**

$$E_{\text{red}} = E^{\ominus}_{\text{red}} - \frac{RT}{zF} \ln\left(\frac{\gamma_{\text{Red}}}{\gamma_{\text{Ox}}} \frac{C_{\text{Red}}}{C_{\text{Ox}}}\right)$$

$$E_{\text{red}} = E^{\ominus}_{\text{red}} - \frac{RT}{zF} \left(\ln \frac{\gamma_{\text{Red}}}{\gamma_{\text{Ox}}} + \ln \frac{C_{\text{Red}}}{C_{\text{Ox}}}\right)$$

$$E_{\text{red}} = \underbrace{\left(E^{\ominus}_{\text{red}} - \frac{RT}{zF} \ln \frac{\gamma_{\text{Red}}}{\gamma_{\text{Ox}}}\right)}_{E^{\ominus'}_{\text{red}}} - \frac{RT}{zF} \ln \frac{C_{\text{Red}}}{C_{\text{Ox}}}$$

### 5.1. Successful Implementation of Data-Driven Approaches

As is typical with manufacturing plants, data-driven approaches rely on multiple IT systems, not only on the level of production but also at higher and lower levels. To achieve sustainable production in LVMP, the successful implementation of these approaches requires a set of necessary actions. Firstly, synergy for implementing data-driven approaches within the LVMP should be created. It is difficult to carry out sustainable production not only without combining various organizational and technical solutions but also without the effective coordination of their implementation. From the point of view of creating and supporting synergy for such implementation, it is important to prioritize powerful data generation and analysis with an emphasis on their manufacturing aspect and the search for data-driven solutions that contribute to solving various problems of sustainable production.

Secondly, an effective regulatory framework should be established at several levels. The most important should be the synchronization of information and communication technologies with creating regulations for the application of data-driven solutions. The implementation of data-driven approaches in large vehicle manufacturing plants must be adapted to its current structure and function. Centralized standardized information support using updated IT allows for setting priorities, determining the hierarchy, and ensuring the coordination of the sustainable production development process at the LVMP. Successful state regulations can indirectly contribute to achieving sustainable production in LVMP if this industry is the largest within the state's industrial complex.

### 5.2. Innovative Sustainable Practices

This paper introduces a data-driven approach for a better understanding of the potential impacts of such trends on industrial parks and their corporations. The proposed method builds on natural language processing techniques to understand the issues raised by the document and a novel topic model and phrase mining approach to understand the complexity of the future megatrends driving the transition to the society of the future.

Emerging trends in vehicle production require manufacturers to improve their production methods to achieve the ambitious sustainable development goals set for 2050. The large-scale assembly of vehicles involves various processes representing specific challenges for environmentally sustainable production. This chapter focuses primarily on the sustainable aspects of the main manufacturing processes used during vehicle assembly, including the involved joining and handling techniques. It discusses current challenges and potential solutions that have the potential to dramatically improve the industrial standards of life for both employees and the surrounding environment in the future. The chapter introduces and discusses innovative green and sustainable practices using natural materials, heat insulation, and simple and natural mechanisms for applications during large vehicle manufacturing operations.

## 6. CONCLUSION

Planet 2050 is a vision for a future where humans and the natural environment flourish together. In Planet 2050, in manufacturing, a method of data sharing to drive a culture of sustainability and ensure that all stakeholders in global communities have a bright future will lead to safer, more productive workforces that contribute to stimulating economies and empowering people, while working within the boundaries of an environment in balance. Although the discussions in this chapter are specific to the Large Vehicle business, the approaches to achieve Planet 2050 can be leveraged across manufacturing and most other industries. We believe the use of data-driven approaches is crucial to ensure we continue to make significant contributions in our journey of addressing the ever-evolving challenges our society faces and the aspirations our society has. We must continue to innovate and maintain a solutions-as-a-service mindset to fulfill our commitments and take care of humanity and our planet for future generations. As a leading corporation, we believe there is a tremendous opportunity for our industry to lead the adoption of advanced technologies and deliver on the promise of increased sustainability. This vision outlines a journey with an interconnected set of actions and plans on converged, pre-competitive solutions to reach the goal of living within the planetary boundaries and creating a future to thrive. What is outlined in this chapter supports the thought leadership consensus around the world to create a world that is inherently regenerative and creates a future to thrive.

### 6.1. Future Trends

The state of the art in Industry 4.0 and data-driven manufacturing is still rapidly progressing, and some forecasts suggest that these developments will have far-reaching and ever-increasing implications. These forecasts are broken down into two main avenues: technology forecast and future stakeholder specifications. With the ever-evolving sophistication of technology, regardless of its specific area or domain of application, the increasing application of AI research and tools will play a major role in shaping our future, including healthcare systems, justice systems, political systems, and public services, being used increasingly to bear the burden of some of the decision-making beyond human capability.

One distinct nuance relative to other domains, however, applies to the manufacturing sector in that the responsibility of satisfying stakeholders beyond industry innovation rests on its shoulders too. This therefore makes data-driven approaches highly relevant in not only improving the prospects of producing high-quality, high-added-value products but also bridging the gap toward the dream of a more sustainable future, where both production and the use of products have increasingly lower carbon footprints and an enlarged set of enhanced circular economy strategies. In this section, we outline some of the possible future trends surrounding the advanced technologies and tools inherent in Industry 4 and data-driven manufacturing and discuss the relevance of stakeholders in our context. Planet 2050 and the Future of Manufacturing: Data-Driven Approaches to Sustainable Production in Large Vehicle Manufacturing Plants

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