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Transforming Manufacturing Plants for Heavy Vehicles: How Data Analytics Supports Planet 2050's Sustainable Vision

Rama Chandra Rao Nampalli[1], Shakir Syed[2], Vishwanadham Mandala[3]

[1]*Oracle EBS and Workday Consultant, nampalli.ramachandrarao.erp@gmail.com*
[2]*Managing Director corporate partners, shakir.syed.microsoft@gmail.com*
[3]*Service Delivery Lead, Cummins Inc, vishwanadh.mandala@gmail.com*

Sustainability is one of the biggest issues of this age, particularly in sectors needing large amounts of energy. Manufacturing plants in the heavy vehicle sector support the production of goods for a planet with growing energy demands set to double over the next 30 years, with approximately 10 tons per inhabitant. Relationships between Environmental Impact (Planet), Economic Efficiency (Profit), and Social Responsibility and Values (People) are well known. Therefore, by bringing together people, the planet, and heavy vehicle goods transportation, the document sets a vision for the sector in Europe in the year 2050 that the company calls "Planet 2050." Aligning the processes and systems within heavy vehicle manufacturing plants, where the set of constitutive elements fall into the categories of planet, people, and profit, to the values of the time for 2050 gives us, and other companies that contribute to "Planet 2050," an advantage in making investment proposals that will underwrite production in the future. The ability to act in this innovative field can have a direct impact on attracting and retaining the employees of the future; securing the well-being of our planet for our future generations; restructuring the heavy vehicle sector in a European energy transformation space and vision; and setting global principles and adjusted positioning for operations in countries worldwide. It is easy for Step 4, with a data analytics approach, to demonstrate that Plant 2050 has been and is in every part of the manufacturing procedures and systems. Manufacturing of the future, in this sense, must be value-added at the people, planet, and profit interfaces for every element of the process. Making data-driven decisions is increasingly important. Measurements of

sustainability show the cost of a problem. Accordingly, proposal innovation needs to reference the solution rather than the problem. In the heavy vehicle manufacturing sector, data-informed analytics can provide insights that align manufacturing best practices with the development of Plant 2050.
Keywords: Sustainable Manufacturing,Data Analytics,Heavy Vehicles,Industry 4.0,Smart Factories,Environmental Impact,Resource Optimization,Predictive Maintenance,Circular Economy,Carbon Footprint Reduction.

1. Introduction

When the Paris Agreement entered into force in late 2016, the fight against climate change reached a new milestone, as now one hundred and ninety-four countries are committed to containing greenhouse gas emissions from causing more than 2 degrees Celsius of global warming. As the largest emitter of greenhouse gasses, heavy vehicles are responsible for roughly 50 percent of terrestrially emitted GHGs and air pollutants. Heavy vehicles are speeding up the effect of global warming. The manufacturing of such heavy vehicles consists of many processes, which require a large amount of raw materials. To ensure the efficiency of this process, genuine data is mandatory. Therefore, data analytics, as an effective tool, is being standardized for rugged heavy vehicle plants. The modern integrated production environment in heavy vehicle plants is highly complex, incorporating a large number of interfaces across processes and partners. Efforts to improve mass customization necessitate manufacturing and supply chains that are robust, agile, and responsive to customer needs, but also resilient in the face of disruptions, sophisticated to accommodate ecosystem thinking and practice, and maintain the long-term health of these socio-technical systems, which includes reducing energy consumption, reducing emissions, and reducing the consumption of critical materials. These are strategic goals. The basis of the theory guiding these paradigms is socio-technical. The 'Planets' utilize a pull-based scheduling policy and focus on visibility and transparency for reducing emissions on an industrial shop floor. Consumption and usage of optimized process times are common practices to reduce the time of each step or operation just to make all the processes synchronize. However, there may be some cyclic subprocesses that take their time and increase the time of each of the processes.Deep decarbonization of the Indian economy by 2050 hinges significantly on the integration of wind, solar, and green hydrogen technologies. With abundant sunlight and strong wind potential, India is well-positioned to harness renewable energy at scale. The government aims to achieve 500 GW of renewable energy capacity by 2030, creating a robust foundation for a decarbonized grid. Solar and wind energy can provide reliable power, while green hydrogen emerges as a pivotal solution for sectors challenging to electrify, such as heavy industry and transportation. By investing in these technologies, improving energy storage solutions, and enhancing grid infrastructure, India can transition to a sustainable energy landscape, reduce emissions, and support economic growth while addressing energy security and climate change challenges.

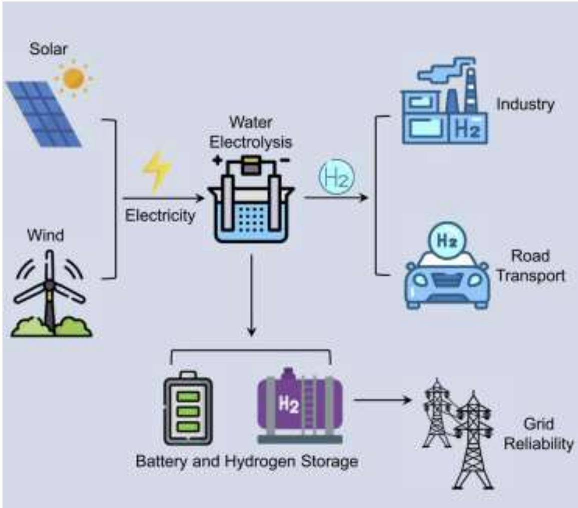

Fig 1: Deep decarbonization of the Indian economy: 2050 prospects for wind, solar, and green hydrogen

1.1. Background and Significance

The EU manufacturing sector is of utmost importance for the production of heavy vehicles as well as for the creation of jobs and GDP. Given today's increasing social concern for global warming and climate change, especially in cities, together with the importance of setting ambitious policy frameworks, the attention to the possible pollution from the transport sector is growing. Heavy-duty vehicles (HDVs) are powered by conventional internal combustion engines (ICEs), which are a major source of greenhouse gas (GHG) emissions and air pollutants. Therefore, the manufacturing sector is under increasing pressure to reduce its impact in the context of Vision 2050. HDVs are expected to nearly double their emissions, reflecting the strong demand for freight transport. The regulatory authorities are increasing the targets in norms that require the trucks to undergo costlier and extended Life Cycle Assessment (LCA) to offset the increased emissions from the ramps. Hence, the transformation of the manufacturing plant is imperative, and it is only possible to achieve this through strong technological utilities.

The manufacturing process of heavy vehicles has undergone systematic transformations over time to effectively cater to the growing demand and competition in the global market. Although various actions have been put into effect, systemic changes have never been made since World War II to reduce environmental impacts. The first industrial revolution started in the 18th century, marking the shift from hand production methods to mechanization, and the first US mechanical plant was built in 1913. Then came scientific management and mass production with the design of the Taylor framework in 1944. The product life cycle is being used to design the assembly plant, and in 1962, the first assembly line for the mass production of vehicles was put into effect, treating humans as machines. The automation in the middle of the assembly line increased the production of vehicles from 6,000 vehicles per 8-hour shift to an astonishing 10,406! Consequently, emissions skyrocketed. All this has driven the perception of heavy vehicle assembly plants towards negativity. Rather, they must focus on positive impacts through systematic transformation and research into business impact. It is only through a focus on sustainable development that this can be achieved. Therefore, the existing plants for heavy vehicles would have to be upgraded to be viable for the next 40–50 years. This can be accomplished if the plant operations align with the Sustainable Development Goals (SDGs) of Planet 2050. A journey of revamping green manufacturing practices can commence. Although HDV cycles are advancing, there is still very limited work regarding the transformation of full-assembly HDV plants. The transformation of existing HDV plants using data analytics is even narrower. This revamping, on one hand, would reduce the vehicle manufacturing impacts to a range of 7,520–30,960 and 1,385–2,730 $gCO2$ per closed-loop supply chains of zero-emission electric vehicles (EVs) and conventional natural gas vehicles (NGVs), respectively. A shortened procedure also stands distinct compared to the longer product life cycles. A major peak in customer demand as well as production demand is hereby addressed. The profit of the HDV assembly line and HDV assembly plant scale up to a staggering 48.6985 million dollars and 218.9465 million dollars, respectively.

Equ 1: Transformer Basics and Transformer Principles

$$\text{efficiency, } \eta = \frac{\text{Output Power}}{\text{Input Power}} \times 100\%$$

$$= \frac{\text{Input Power - Losses}}{\text{Input Power}} \times 100\%$$

$$= 1 - \frac{\text{Losses}}{\text{Input Power}} \times 100\%$$

1.2. Research Aim and Objectives

This research will investigate the development of a digital twin capable of supporting decision-makers in manufacturing plants that produce heavy vehicles. The goal of the digital twin is to support the attainment of a more sustainable society by reducing the environmental burden of products and services. Three papers will be produced as a result of this effort; the first paper will present a comprehensive literature review to evaluate contemporary manufacturing in the heavy vehicles segment and help overcome the challenges they face in improving environmental performance. The next two papers will focus on the development of the digital twin and the real case of the industry in which the digital twin developed will be tested.

In summary, the literature review will investigate two central dimensions. The first of these is the primary issue in the production of heavy vehicles in the real world today. As an example of non-value-added activities, it cannot be seen as the cause of increased physical efficiency. Introducing the digital twin to assembly lines will reduce the time and improve the environmental performance of assembling light commercial vehicles. The primary aim of this research was to address the following three closely related objectives:

- To explore and identify the challenges currently faced when attempting to integrate data analytics to support a durable disruptive technological solution that can be implemented in a heavy vehicle manufacturing plant. Therefore, we have addressed an overarching vision to develop a robust pathway for deploying data analytics aimed at furthering the sustainable manufacturing of heavy vehicles. Designed to evaluate the current adoption of data analytics, we explored some of the key challenges experienced by companies and other associated industries. - By creating an overview of the role data analytics already play and how they contribute to operating transformative production and innovative process solutions, we proposed a system to transform operations within the installed base. In doing so, we introduced three examples that support the integration of data analytics to drive sustainable heavy vehicle solutions. - Viewed as the long-term outcome of this research, we argue that the exploration of these examples will enhance the understanding of how the deployment of a data-analytic solution can drive mature industries toward a more competitive future. Focusing on the innovation needed now in preparation for the future calls for technology and cross-sectoral leadership vision to collaborate and achieve these truly innovative accelerated changes. This is interdisciplinary research and will seek to understand the system and organizational dynamics and the affordances of data analytics using case study evidence and legal and regulatory knowledge.

2. Current Challenges in Heavy Vehicle Manufacturing

The manufacturing of heavy vehicles is faced with several serious challenges: degeneration of the environment, resource depletion, waste generation, and an increasing number of process parameter settings for optimizing fuel consumption and emissions. From these statements, it is clear how critical it is, as well as how urgent it is to make vehicle manufacturing sustainable. However, the current situation reveals that the manufacturing plants themselves, where the main products are made, are not environmentally friendly and are very resource- and time-consuming. This forces them to produce high-quality, reliable vehicles at a high cost, making it difficult for them to compete with other means of transportation. That is why it is important to address the aforementioned problems and work on offering efficient solutions. The purpose of Planet 2050 is informed and driven in part by economic considerations, as organizations need to be profitable.

In an ideal world, a manufacturing plant would operate without causing environmental degradation or resource depletion. Its processes would be organized in such a way that contemporary, as well as future, vehicle models could be manufactured without excessive costs or wastage of materials. This is not difficult in the case of correctly managed material flows; however, in practice, these can be very complex because they can lead to an excessive concentration of particles or contaminants, which may result in items becoming defective. Consequently, material flows may have to be diluted, leading to excessive volumes of used polished slurry or coolant. Such challenges must be addressed to guarantee the sustainability of a manufacturing plant for heavy vehicles. Ironically, the advancement of measurement techniques has complicated the problem of waste and by-product streams. The main advantage of the new technologies is that they provide more information about the conditions of the superior and inferior materials, but the transmission and storage of this information is time-consuming and resource-intensive.

Fig 2 : Challenges and opportunities with electric vehicles

2.1. Environmental Impact

Creating heavy vehicles such as agricultural machinery and construction equipment involves two key manufacturing steps: forming the desired components and joining them. Heavy vehicle manufacturing accounts for 2% of the world's fossil fuel consumption, generating huge amounts of CO2 emissions. The production of raw materials and assembly of vehicles together generate over twice as many CO2 emissions as vehicle use during field operations, which is the main lifetime source of CO2 emissions. A further 4 liters of fossil fuel are burned for every ton of steel produced, while released pollutants lead to acid rain, which harms plant and aquatic life. Equipment manufacture is energy intensive; metal casting, cold forming, and machining are energy intensive, while waste heat is created during coating and soldering operations. Forming vehicles also entails the stock removal or reworking of 80% of the raw steel; this machining time results in a 35% lead time. It is important to replace metal, oil-based plastic, and ceramic components because of resource depletion, massive energy demand, and pollution-induced by mining the required elements. Clay, as a ceramic, is a highly energy-demanding component in what can often be a ceramic process, which can take over 24 hours to form in an oven used at temperatures of 900 °C.

Consequently, the heavy industrial machinery equipment sector has generated environmental concerns as it heavily relies on the mining, burning, and refining of oil, producing large volumes of CO2 with significant associated waste generation, and is responsible for long lead times. Manufacturing facilities, therefore, need to improve equipment, processes, and management procedures to satisfy future environmental regulations, allowing the manufacturing of more sustainable vehicles. Practitioners and policymakers have started identifying such challenges. For example, stricter environmental regulations have increased demand for manufacturing processes that produce plant and environmentally-friendly products. This involves the manufacturing industries excluding or reducing the use of hazardous materials and increasing the recovery, reuse, and recycling of waste. Industry, therefore, must discover efficient materials, designs, and manufacturing processes that will enable the creation of environmentally neutral, long-life products, in what is called a circular economy. The use of vibration-assisted processing to generate longer-lasting materials, at appropriate vibrational loads, has demonstrated an increase in micro-hardness, surface roughness, surface layer nitrogen content, and an enhancement in the residual stress field, which are potential suggestions. Supply chains need to be recombined to continuously adapt material availability and to mitigate long-term environmental degradation; a circular economy paradigm seeks to close and retain materials in a tight loop. The goal of a circular economy does not seek remanufacturing and reconditioning, as this does not fully utilize the component, which may have further possibilities with different characteristics; remanufacturing and reconditioning processes negate part recovery. Instead, approaches should be geared towards cascading materials for further life usage; after a period of use, materials are extracted from products and systems and then inserted at their final resting place, such as desorbed in an idle landfill, ground, until powdered, or landfilled until materials purchased, can eventually be harvested, creating evils that spiral into a vicious cycle. To achieve this, the raw materials supply chain of goods is required, enabling the original equipment manufacturer and supplier to move from using any source of material, including brand new, unused stock, to an assembly and end-user using second-life components, possibly reducing lead time but extending the remanufacturing process lifetime.

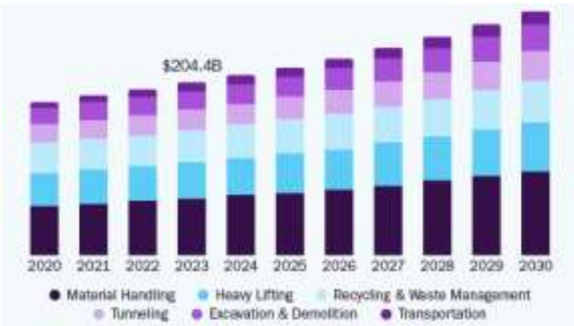

Fig : Heavy Construction Equipment Market

2.2. Efficiency and Productivity

Manufacturing heavy vehicles is complex—plants require hundreds of production processes, logistics, and skilled human workers. These processes are often highly interdependent, and errors in one part of the plant can accumulate and propagate through the process chain. Thus, inefficiency in any part of the plant can lead to high costs; slowing down any part of a process could lead to downtime and resource expenditure. All these costs eventually lower the profit from each vehicle sold. Furthermore, if people, energy, and materials are used wastefully, manufacturers cannot meet sustainability goals.

Generally, inefficiencies in plants are referred to as operational bottlenecks, since these are obstacles to production, and societies in which industries operate are often referred to as bottleneck economies. This means that if heavy vehicle manufacturers produce at outputs Y, where possible output $Y^* > Y$, this leads to suboptimal use of resources. In the long term, this suboptimal use could lead to corporations being less competitive in the international market. In other words, for every vehicle manufactured, or any other production process that is also relevant for the environmental model, there is also an opportunity cost: perhaps some better actual alternative in the future? So efficiency is key to the success of the cross-impact of the domain: the harmonization or true sustainability of the global economy, including its industrial sectors. Clearly, to deliver on the sustainability vision, new, more accurate, quantitative, direct measures of productivity changes between and within manufacturing plants are required.

Data-driven strategies using analytics can provide insights into which points may be improved. More importantly, however, they will change the decision-making process; knowledge, such as production status, will be used to make decisions that have economic consequences. Data analytics can help people quickly and accurately assess the options available. Furthermore, data analytics can be used to reveal the cause and potential solution to root causes of any suboptimal production performance, through analysis in the shape of clear metrics and ratios such as economic productivity and resource productivity measures. From an industrial perspective, therefore, increasing these outputs while keeping constant the input will lead to a decrease in unit costs. Given the supply factor in the plants to maintain the factory goals, better production can be related to better emission control, and thus reduced footprints of the vehicles, which improves sustainability and increases efficiency.

3. Role of Data Analytics in Sustainable Manufacturing

This theme is quite expansive in the operations and services if we expand the boundaries of "physical components" to interconnected systems that support them, including the workers operating the machines, the managers running the plants, the users operating the equipment, and the stakeholders interacting with the exposed products. The goal of digital science in sustainable manufacturing is to provide insight and drive decision-making that reduces waste and improves efficiency, and to provide early warning of anomalies that could lead to environmental harm or damage, as well as unsafe operations. Ultimately, these manufacturing decisions are aligned with the challenge of making sure the planet survives and even thrives in the future. The performance of any manufacturing system in all of these dimensions, including the machinery, workers, outputs, and services, depends collectively on the decisions made. The role of digital science, and in particular data analytics, is to provide new and better insights based on the techniques described, and to test its ability to do so that will support sustainable outcomes. Importantly, we have seen that manufacturing analytics of various forms have become more mainstream and can depend on technical solutions, such as machine learning, practical techniques, such as KPIs and financial indicators, or deeper, scalable modeling approaches that connect these technical capabilities to deeper decision-making. The thoughtful application of many of these tools to the heavy vehicle manufacturing space demonstrates the problems it can address. There are several reasons this may be desired, with the greatest need being to address the numerous manufacturing process disruptions, including those resulting from the pandemic, and those making it difficult to staff factories. As our planet invests in and desires infrastructure improvements, including smart and efficient vehicles, technology provides excellent opportunities to look more deeply within manufacturing systems to investigate disruptions to performance, such as the supply or extraction of minerals that support factory infrastructure, such as heavy vehicle machinery, human staff, financing, or transportation issues, and the implications for the climate and environment of the output produced, whether it is a partially assembled frame or a complete vehicle. For instance, telltale signals of factory performance can be a marked increase in carbon emissions or energy consumption over the short term, as well as disruptive bursts in any of the stated inputs and outputs. Thus, we position this work on the capability of data analytics to narrate the challenges on the factory floor in a readily interpretable language. These types of narrations are useful as a basis for action, for discussion, and for developing new areas of expertise that are more desirable in a manufacturing future.

Fig 3: Data Analytics for Sustainable Supply Chain Management

3.1. Definition and Scope of Data Analytics

At the heart of Industry 4.0, one finds data analytics that enables continuous and sustainable enhancements throughout the various phases of the product life cycle. The essence of data analytics lies in uncovering the underlying value hidden in large datasets. In manufacturing practices, data can be found and collected at various levels of the production ecosystem, such as from shop-floor equipment, supply chain management systems, customer relations, and human resources systems, to name a few. Operational and business activities about the analysis of this data are considered under the banner of data analytics. Broadly, the analysis can be classified into three main types:

Descriptive Analytics: Utilizes the current and historical data to provide insights and trends into the current state of affairs. Predictive Analytics: Uses the current data to estimate future trends and the likelihood of particular outcomes. Prescriptive Analytics: Takes input from descriptive and predictive analytics to explicitly recommend some action or outcome. The data analyzed can also take various forms, such as structured, semi-structured, and unstructured data. The application of such data analytics techniques to heavy vehicle manufacturing is a significant topic because of its potential to unveil insights for better decision-making that are not just incremental but transformational. Such insights can span across the entire plant value chain and lead to actionable outcomes, such as the minimization of operator fatigue and reduced rework rate. Although data enables analytics, it is the quality and integrity of the data collected that drives reliability and relevance within analytics. High-quality data with clear metadata leads to a greater level of trust by the decision-makers in the system, contributing to effective human-data system interaction. Even though there are technological advances in capturing and storing more data, the veracity of the data stored may be quite low. This is why sometimes extracting the right insights becomes difficult. However, it is also anticipated to be the single most powerful enabler in achieving the sustainable goal of Plant 2050.

The purpose of this subsection is to agree upon and define a shared understanding of relevant terms throughout the remainder of this text. Data analytics are known under various names, including data mining, knowledge extraction, big data analytics, business intelligence, advanced analytics, machine learning, and statistics. However, for this text, the term "data analytics" will be used as it is more broadly understandable to organizations that are new to leveraging data for operational improvements. Data analytics is the scientific process of analyzing data to find hidden insights, trends, patterns, and values to plan better, improve operational and business activities, and support decision-making. Insights are the key to decision-making and are of two types: something that was not known but changed management decision-making or insights that were not thought about since the focus was too narrow or the age of the data being analyzed is outdated. The insights that are to be uncovered and used to transform the heavy vehicle or heavy equipment are the former types of insights. Data is the specific facts and discoveries we are after, while insight is the fact or discovery that we were not aware of until we saw our data. The insight is the 'wow'.

Equ 2: Computing ROI based on a point in time

3.2.Applications in Heavy Vehicle Manufacturing

Manufacturing heavy equipment today is probably the most challenging era this industry has ever faced. You need to deal with downtimes and unplanned breaks after every incident. In other words, when something is discovered broken, it is already too late. Predictive maintenance, with its data analytics component, can predict what is likely to happen and therefore significantly reduce these downtimes. Not only for predictive maintenance purposes have data analytics been considered highly helpful; the insights drawn from historical data can offer great opportunities in other applications as well. These can, for example, be used to either improve the plant itself, lower costs or increase work safety. Predictive analytics can also provide plants with an idea of what the market demand is likely to require. Moreover, this tool offers good predictive capabilities, including forward-looking data, and may improve forecasting accuracy, thus enabling a data-driven agile manufacturing approach as supported by Industry 4.0.

A leading global supplier of bearing technology is already making use of the capabilities of predictive maintenance in their products. Using a mix of technologies, including connected sensors, advanced encryption, and the power of cloud-based data analytics, the company can effectively monitor models of heavy industrial vehicles, such as trains, and predict when components should be scheduled for maintenance. This proactive approach helps to avoid failure downstream in the process as well as unnecessary costs for scheduled checks when not needed. Deviating vibrations of train wheels can be detected with machine learning methods that have proven that on-site analysis is just as good as laboratory standard tests while being faster, simpler, and cheaper. The newly built heavy multi-purpose vehicle that thoroughly measures and sets the wheels of light rail vehicles does just this. A full-line supplier of bearings has been on track for over 100 years. The company is the market leader in passenger coaches and freight cars and is also the leading original equipment supplier of complete wheel sets for light rail vehicles.

4. Case Studies and Best Practices

Successful examples of implementing data analytics at manufacturing plants for heavy vehicles are presented in this section. They are illustrative data analytics supporting the manufacturing report in our study and demonstrate best practices in applying data analytics and potential strategies to overcome the challenges of this transformation to sustainability. This analysis provides insights for others inside and outside the sector, illustrating how companies around the world have brought data analytics to bear on very different problems throughout the sector. Some have found wonderfully simple ways to save fresh water; some trace every part back to its source amid a morass of different suppliers. Some focus more on short-term cost pressures, with fleet efficiency or just-in-time manufacturing analyses; others are more forward-looking, implementing sophisticated predictive maintenance analytics for autonomous vehicles.

Our manufacturers have told us, time and again, that sharing these case studies will help change-making ministers and officials see what is possible and make companies around the world realize that they too can start this transition to re-engineer efficiency across the sector. In this sense, this isn't an analytical report. It is designed to inspire change. Though each of our case studies is unique, there are lessons and recommendations to be drawn from them that are broadly applicable. All our manufacturers faced resistance during implementation, especially from those not aware of the potential of data analytics to effect transformation. Entrusting crucial data to a proprietary system on-site with a separate company, many noted, also required a leap of faith. Despite this, no manufacturer said they would not have gone through with the process, and some are even thinking of scaling it up. In focusing so intently on best practice, our study is necessarily reductive and risks downplaying other considerations, such as the level of corporate organization and managerial talent required, which were rightly pointed out to us as causes for concern. However, we have attempted to paint as broad a picture as possible to establish the feasibility of data analytics across the entire heavy vehicle sector.

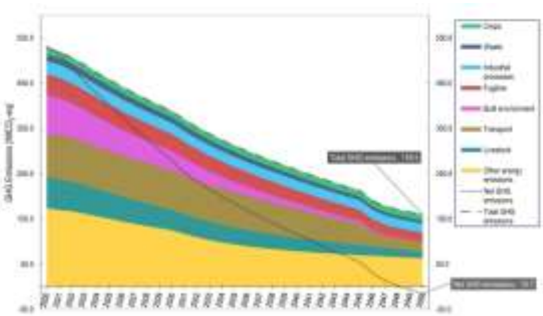

Fig 4: Modeling six sustainable development transformations

4.1. Examples of Data Analytics Implementation in Manufacturing Plants

Case Studies Several case studies describe industrial implementation experiences of data analytics in manufacturing plants for heavy vehicles. These papers are an important source for telling individual stories about companies using data analytics to drive efficiency in assembling processes of their products. For instance, the implementation of data analytics from a top manager and production manager perspective in a worldwide operating traditional producer of traction and rolling stock systems based in Switzerland is revealed. The discussion includes the strong combination of operations research and data analytics as enabling technologies for determining system interdependencies between assuring the life cycle of entire systems maintenance and a production control system. Additionally, the leap from a 3D design to a 3D production by using data analytics and the digital companion approach at a truck manufacturing and assembly site of the oldest industrial company in Germany is also shared. The detailed presentation of the specific process and manufacturing technologies helps to understand what is behind the abstract statement of an objective. In addition, a systematic methodology that considers a unique combination of methods when applying data analytics in heavy industries to cater to the peculiarities of these industries is introduced.

Similarly, the implementation of data analytics driving efficiency in an intercontinental truck manufacturing company is presented. The case study discusses the work of transforming the manufacturing system and managing improvement and maintenance while monitoring logistics and service quality variation with the use of data analytics. Another view of the same company aimed to implement data analytics for anomaly detection in a production line for heavy trucks. This case study focuses on detecting and verifying anomalies with high certainty. The potential of data-driven Reduced Order Models in improving production processes of extruded aluminum profiles for the transportation sector is analyzed. A novel framework that integrates hybrid physical and data-driven techniques for predicting energy consumption and carbon emissions in a steel manufacturing process is deployed. The case study shows that data-driven techniques can provide improved energy and carbon surrogate models when compared to a physics-based approach while being less computationally expensive too.

Fig 4 : Big Data Analytics in the Manufacturing Industry

5. Future Directions and Recommendations

The manufacturing of heavy vehicles has the potential to greatly impact business and society. The analysis and practice of data analytics in manufacturing are still emerging and present future directions and recommendations for both. Future directions in heavy vehicle manufacturer research and practices are anticipated to further align with sustainable manufacturing, digitalization of the supply chain and products, increased collaboration between industry, customers, governments, and research organizations, and the significant role of innovation and entrepreneurship in business and manufacturing practices. Based on these trends, we present recommendations and future directions for manufacturers that will aid them in being proactive toward the creation of a sustainable manufacturing framework for heavy vehicle production. Recommendations for heavy vehicle manufacturing are directed toward the adoption of innovative business practices and relationships that align with the pursuit of sustainability at the manufacturing plant. The strategies focus on ongoing continuous change and improvement for manufacturers and suppliers; collaboration with industry to build trust and establish ongoing relationships, industry-wide sustainability objectives, knowledge sharing, and the creation of an industry research group; the necessity for investment in at least three areas: ongoing knowledge and implementation of new technologies in manufacturing; ongoing organizational development and staff training; and support for implementations with education and knowledge exchange. It is also advisable for heavy vehicle manufacturers to adopt a proactive strategy towards changes in the manufacturing of heavy vehicles to enhance the company’s proactive sustainability stance. Barriers to recommendations generally relate to mindset, and it is advisable to apply change and innovation readiness strategies based on the primary issues to enhance the enactment of the recommendations. As is evident from the findings, changes involving new process technologies and the strategic implementation of data analytics are required in the heavy vehicle manufacturing process. New levels of innovation and knowledge sharing are presented in the strategic implementation of advanced practices that drive industry-wide sustainable transitions. Ongoing, proactive change and innovation adaptation strategies are also advocated. Greater knowledge and understanding of heavy vehicle manufacturing processes and data analytics, in combination with the sustainability impacts of various stages of production in manufacturing companies in the heavy vehicle sector, are also crucial. It will assist in demonstrating the interplay between areas of sustainable manufacturing research and driving for continuous adaptation and innovation towards new research and industry practice through industry-university collaboration. The manufacturing of heavy vehicles presents a significant opportunity for the business and societal realm, as well as for appropriateness among sustainability scholars and professionals. Data suggests that automotive manufacturing will face a tough time in the coming years, especially in the next 5 to 10 years. This is a time of change where manufacturers and suppliers are constantly looking for improvements. With this attitude and through trust and industry collaboration, proactive change and support are currently adopted by medium-to-low-tech industry partners to implement new solutions.

Fig 5: Future Directions and Recommendations

6. Conclusion

The objective of this paper is to discuss Industry 4.0 as a solution to problems faced by heavy vehicle manufacturing plants transforming into sustainable manufacturing plants. Innovative data-driven analytics practices may become the driving force for sustainability in the heavy vehicle sector. Thus, everyone involved in this sector needs to recognize the potential significance of data analytics in contributing to sustainability. The results of this study are therefore extremely important for the heavy vehicle manufacturing industry pursuing improvement in five sustainability areas. Transforming manufacturing plants with a tradition of producing products in heavy vehicle manufacturing is a complex issue that must take into account many interdependencies. The challenges and transformations that are taking place suggest that the industry may become unsustainable. Such an industry can recognize current and future limitations and think sustainably, and it strives to continuously improve, follow, and apply state-of-the-art solutions. Technological innovation with smart solutions could increase the technical and economic efficiency of systems, thus providing a higher standard of living. We found that it is possible to help decrease the negative impact of heavy vehicle products. The changes, determinations, and enlightenment suggest that in the future, there should be more attractive and efficient solutions. To succeed in achieving these recommendations, widespread support and understanding of sustainability are needed. In conclusion, if heavy vehicle production focuses on state-of-the-art technology, it may be higher in demand, have a longer life, and feature more customized and efficient solutions to provide a sustainable environment. This is a critical call for the heavy vehicle industry to embrace state-of-the-art data-driven analytics.

Equ 3: Define & Measure Centrifugal Pump Efficiency

$$\text{Pump Efficiency} = \frac{\text{Output}}{\text{Input}} = \frac{\text{WHP (Water Horse Power)}}{\text{BHP (Brake Horse Power)}}$$

$$\text{WHP} = \frac{\text{Head} \times \text{Flow} \times \text{Specific Gravity}}{3960}$$

$$\text{BHP} = \frac{\text{Head} \times \text{Flow} \times \text{Specific Gravity}}{3960 \times \text{efficiency}}$$

6.1. Future Trends

Emerging trends are expected to shape how a heavy vehicle manufacturing plant operates. Events and capabilities related to emerging sustainability trends and emerging data analytics trends, including artificial intelligence, technology and model developments, the Internet of Things, and the circular economy. It is anticipated that new technologies like artificial intelligence will be used in combination with traditional manufacturing methodologies for continuous assessment of new training data at the same time as processing incoming sensory data. It is anticipated that the increasing requirements for real-time process control and the ability to change operations will continue. This is partly due to increasing mixed product and cooperation between heavy manufacturing and the final stages of vehicle completion, including electronic and software management.

Maintaining the beginning of migration towards increased use of resource efficiency methodologies in manufacturing, including an increased emphasis on circular economy principles, makes relevant industry backgrounds beyond automotive or workshops that control large heavy industrial equipment. A manufacturing plant links to one of the world's major suppliers of sustainable transport systems, including trains. These new facilities can produce an example of both the opportunity and the productivity gains available with new plants and new capabilities in an increasingly digital world. Preparing for a future of extreme short-term agility to deal with large variations in the sparsely mixed production schedules. These changes require major strategic real-time adaptation. To be reactive, strategic investment and continuous investment in data management capabilities, including artificial intelligence and machine learning, are required.

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