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Big Data Analytics In Heavy Vehicle Manufacturing: Advancing Planet 2050 Goals For A Sustainable Automotive Industry

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Abstract
The automotive industry has embraced the shift towards more sustainable solutions both in terms of the products developed and the production methods. Given its scope, the heavy vehicle manufacturing sector has a huge opportunity to contribute towards reducing the environmental impact of vehicle production. The vehicle manufacturing process is complex, with several parts and subsystems being assembled to create the finished product. The amount of energy and materials required for vehicle manufacture has driven the industry towards identifying opportunities to reduce the carbon footprint of production processes.
One key enabler in this quest has been the ability to collect and process big data. Global trends across many industry sectors indicate an increase in the number of sensors and data collected, processed, and stored. This trend correlates with the lowering cost of sensors, advances in computing, and the increase in data with which to train machine learning models. The primary relevance lies in the manner in which machine learning techniques and related algorithms can capitalize on big data collected from the heavy automotive manufacturing industry to advance the environmental goals set forth. Indeed, this offers three high-level goals designed to support vehicle innovation desired for 2050, which ultimately addresses the need for lower carbon emissions and energy consumption.

Keywords: Sustainable solutions, Heavy vehicle manufacturing, Environmental impact, Vehicle production, Carbon footprint, Big data, Sensors, Machine learning, Energy consumption, Lower carbon emissions.

1. Introduction

The article presents a new big data analytical framework that supports multiple manufacturing decision-making activities in the context of heavy automotive industries. Heavy vehicle manufacturing contributes a significant amount to global greenhouse gas emissions via the manufacturing, use, and disposal of these vehicles. As the global community agitates for nations to reduce their carbon footprint to help accomplish the goals of limiting global warming by 2050, the automotive industry is compelled to contribute to these goals. Through collaborative partnerships, the automotive industry is identifying new technologies and practices for sustainable manufacturing.
As a responsible industry stakeholder, heavy vehicle manufacturing is thus harnessing big data technologies to address its prominent and long-term challenges. To achieve this, manufacturers are discovering insights from their big data sources, such as supply chain management data, customer relationship management data, vehicle fuel and energy data, safety data, vehicle health monitoring data, warranty data, and vehicle design data. Big data analytics is the method by which this discovery is facilitated. While preceding studies focusing on automotive industries demonstrated the potential of big data analytics as a support for production line and supply chain management, the impacts of big data analytics capabilities on the critical components of a heavy vehicle manufacturing enterprise are less well understood. Consequently, an enhanced understanding of big data analytics method support to essential heavy vehicle manufacturing enterprise activities is needed and justified.

Equation 1 : Production Efficiency
To measure the production efficiency of heavy vehicles:

$$\text{Production Efficiency}(PE) = \frac{\text{Total Output}}{\text{Total Input}}$$

Where: Total Output = Number of vehicles produced
Total Input = Total hours of labor + Raw materials used + Energy consumed

1.1. Background and Significance

The automotive industry is facing unprecedented change pressures from society. Governments and consumers are demanding environmentally friendly vehicles that are pollution-free, have low energy consumption, and are fossil fuel independent. Restrictions on emissions and the move towards renewable energy-based propulsion systems are just part of the challenges that automobile designers and manufacturers face. The use of this energy to power the vehicle in a sustainable, economical, and safe way also represents significant challenges. Sustainability has become a key element within manufacturing strategy and practice in the automotive industry. Issues such as process optimization, condition-based estimating, reduced material usage, and energy reduction are hallmarks of best practice. Advances in heavy vehicle fuel efficiency and sustainability are integral aspects of achieving long-term environmental goals.

Electronic control systems within heavy vehicles have generated immense interest among manufacturers and diagnostic tool developers. Modern manufacturing and digitization are fully addressing the provision of in-production diagnostics and solving optimization problems such as scheduling, resource allocation, and production costing. However, minimal work has been done to integrate manufacturing, processing, diagnostic, and environmental/sustainability information. The accurate and swift fusion of these data sources and their analysis could generate significant production and life-stage benefits. For instance, in-production diagnostics data should be used to update fleet or in-service information models, providing predictive performance and lifetime data and cybersecurity. Such an integration approach would provide a broader learning context, especially in the analysis of heavy vehicle lifetime and during the critical handoff from the manufacturer to operators, which is important when focusing on long-term cost reductions, performance improvement, safety, and aftermarket fleet operations management. By knowing how their vehicle has performed in service, operators will be able to minimize any negative impact on the environment.

Fig 1: Big Data Transforming the Automobile Industry

1.2. Research Objectives

The primary objective of the research is to develop a locomotive manufacturing big data framework that defines: a) the individual and collective shared values of the stakeholders of the heavy vehicle sector including the employees, suppliers, logistics providers, consumers, and the wider community; b) the critical and synergistic enablers for the big data framework, aggregating the networking mode, data resource capabilities, and the technical and organizational capabilities; c) the potential performance measures for the examined framework managing uncertainty and complexity. The secondary research aim is to fortify the theoretical foundation regarding the nexus among big data, a quadruple helix model of innovation comprising government, business, academia, society, and stakeholder management. Key research questions addressed by the research investigation are Q1. To what extent does the integration of big data analytics contribute to the Sustainable Development Goals? Q2. What is the state of research on big data systems described in the context of the heavy vehicle sector? Q3. How does experimental analysis help in understanding the benefits of various machine learning methods? Q4. Can the implementation of big data in a specific industry reflect the level of techno-social development? Q5. What are the potential risks and unintended ethical and data security consequences of big data?

2. Big Data Analytics in the Automotive Industry

In the last two decades, significant amounts of data have been produced throughout the entire automotive production lifecycle. Ever more informed customers act in a volatile market exhibiting swift shifts in customer demand and preferences. The global automotive industry has increasingly become an indispensable part of the world's economy. It has contributed greatly to industrial growth and sustained improvement in personal mobility. As the automotive industry moves toward a communication era, innovative technologies such as big data analytics, machine learning, knowledge-driven manufacturing, and intelligent transportation systems will play core roles in the advancement of related issues. Research involving big data analytics in manufacturing, which covers the entire automotive supply chain and production lifecycle, including customers, freight, vehicle assembly, and vehicle-end usage, has attracted tremendous attention.

This research leverages big data to take advantage of business analytics and related insights regarding a big data research roadmap. Presently, both descriptive and diagnostic studies have already been initiated. Advanced big data-related predictive analytics are currently in practice, such as assisted risk analytics in global sourcing and global optimized markets, real-time logistics planning and control for first-tier suppliers, and adaptive production and manufacturing operability of complex production processes. Intelligent transportation systems are another context-specific area, designed to promptly announce traffic congestion and alert vehicle drivers with alternative routes to prevent damage to the value chain. Insightful big data applications that conduct descriptive, diagnostic, predictive, and prescriptive levels are still in the proof-of-concept stage. We envision that the actual applications of advanced business insight and drivers for gainful initiatives presented in this research will play an important role in guiding the strategic investments of stakeholders and may act as an innovation machine and a change catalyst to drive business performance, and especially to help alleviate some key challenges of the automotive industry.

Equation 2 : Energy Consumption
To analyze the energy efficiency in manufacturing:

$$\text{Energy Efficiency}(EE) = \frac{\text{Total Output}}{\text{Total Energy Consumption}}$$

Where:
Total Energy Consumption = Sum of all energy sources used in production (electricity, fossil fuels, etc.)

2.1. Overview of Big Data Analytics
To survive and grow in today's highly competitive and technology-driven marketplace, manufacturing companies need both traditional quality, efficiency, and productivity improvement strategies and new advanced manufacturing strategies that emphasize adaptability, human-machine collaboration, flexibility, and precision. The newly boosted way of driving by connected, electric, automated, and shared mobility systems consolidates both car sharing, autonomous driving, and road infrastructure communication demanded by consumers globally, which are also supportive and eco-friendly through integrated information and automated cloud-based smart factories. The usage and adaptation of Big Data Analytics is a potentially game-changing tool that may realize the advanced adoption of massive datasets usually deriving from vehicle internal computers, logistics, assembly lines, suppliers' capabilities, and stakeholders' expertise to further key enablers for car production.
When utilized along a digital twin of the product-process system, evolutionary artificial intelligence algorithms, the internet of things, and a knowledge base of engineering design solutions, Big Data Analytics may be the backbone for service- or product-centric paradigms, design for additive and advanced manufacturing, manufacturing for additive manufacturing, and assemble them with near-zero defects, which is the core enabler for circular business models required for the planet 2050 vision: to decrease the amount of waste and pollution, to curate lifelong well-being and healthy human settlements. The purpose of the paper is to depict a comprehensive Big Data Analytics framework to carry out before, during, and after processes for data searching, storage, and programming control. Specific capabilities for utilizing machine learning and artificial intelligence will be highlighted, used to improve the inspection process, retrofit production cells for human workers and industry 4.0 capabilities, configure and balance production lines, justify logistics routes and subcontractor integrity for enabling business models required by the global key enablers for the replacement of traditional internal combustion engines. To illustrate how Big Data Analytics can be deployed, a case study from the off-highway automotive industry will be depicted.

Fig 2 : Big Data Analytics Opportunities in Electric Vehicle to Transport Oriented Smart City

2.2. Applications in Heavy Vehicle Manufacturing
IoT has led to a profound data explosion over the past couple of years. The connected heavy vehicle ecosystem benefits from more knowledge generated and more data generated from these assets. Big data analytics applications like predictive

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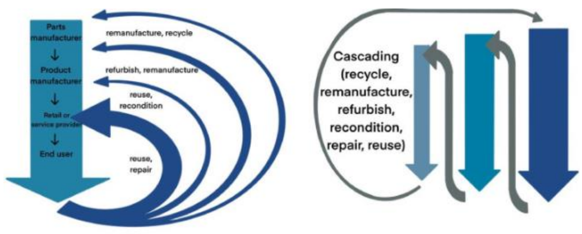
maintenance, fuel consumption optimization, vehicle skid risk assessment, and advanced route planning have huge potential to drive the heavy vehicle ecosystem. Heavy vehicle OEMs would like to replace the existing preventive maintenance approach with advanced predictive maintenance technology. Predictive maintenance can help optimize work planning and monitoring, reduce maintenance costs, and increase the average running time of their vehicles. The operational use of heavy vehicles is very different from the passenger car park by OEMs, with most operators working 24/7 in extreme conditions. Skid risk assessment is very critical for heavy vehicles, especially in mining. Before the creation of the mining machinery, most of the mines are assessed and tested to ascertain the truck risk level of these regions, and these results are also utilized by the Advanced Driver and Driver Map Planning method designed for mining dump truck operations in platinum mines underground as a reference layer input. Subsequently, via optical flow and ultrasonic sensors, localization, and obstacle state detection are realized. ADAP can have many objectives, including the immediate reduction of the level of truck accident risk, task priority, and collision avoidance behind the driver's line of sight between robot vehicles and humans. This paper also offers a cloud-based decision-making platform for all tasks for collective use by several vehicle drivers or users. Finally, platform system sustainability guarantees that such technology is transferable, scalable, adaptable, and flexible for more underground mining applications. The experiment shows a substantial reduction in the collision rate between robots and humans, and the efficiency of ADAP is close to 85%.

3. Sustainability in the Automotive Industry

3.1. Introduction; Sustainability in the Automotive Industry; Significance of the Study; Organizational, Social, and Environmental Performance Parameters; The Benefits of Big Data Analytics; Research Objectives 3.2. Heavy Vehicle Manufacturing and Future Sustainability Requirements; Interplay between Ethical, Human, and Social Factors 3.3. Manufacturing Systems Attributes; People; Sustainable Lean Manufacturing; Processes; Advanced Manufacturing Technologies; Aiding Technologies; Physical Technologies; Simulation-Driven Smart Assembly; Online Quality Control; Automated Line Balancing by Big Data Analytics; Collaborative Robots 3.4. Discussion 3.5. Future Work and Conclusions; Future Work; Conclusions; taken to achieve Big Data Analytics in the sustainable lean manufacturing of heavy vehicles. 3.1. Introduction The automotive industry is increasingly confronted with achieving sustainability, or corporate sustainable development from a new theoretical and strategic perspective. Most major global companies require robust systems of auditing and accountability for the quality, environmental, and social domains, in line with stakeholder values to deliver positive returns for the shareholders. For a long time, their business processes reflected trade-offs among the three domains, a practice that has produced economic value, but also a series of misleading and unsustainable behaviors in all three domains. In response, a set of management principles has been developed to guide an organization and provide processes to ensure that the alignment between the organization's behavior and the probable requirements of the multiple stakeholders of responsible policy are guaranteed, thus describing a way by which good management can create good governance. These management principles are often built within a set of Objectives and Key Results and increase the pressure on embedded business models to focus on 'total quality with objective costs', the real dignity of the goods and services, estimating their dissipation over time, while monitoring the connections between prime cost, selling price, and the actual decision-making forms, deepening the negative versus positive impacts on individual behavior.



a. Regenerative flow is enabled by closed-loop flows (within a supply chain) enabled by circular supply chains. Source: (EMF, 2014; in Batista et al., 2018)

b. Regenerative flow is enabled by Open-loop flows (across supply chains) enabled by circular supply chains. Source: (EMF, 2014; in Batista et al., 2018)

Fig 3 :Automotive Industry's Circularity Applications and Industry 4.0

3.1. Importance of Sustainability in Heavy Vehicle Manufacturing

The concept of sustainability relates to many facets of industry, not just in the context of long-term company viability, but also in terms of how raw materials are beneficially utilized and in the reduction of pollutants and adverse environmental impacts from manufacturing activities, whether these are accidental or deliberate. However, the most pressing and immediate concerns come from manufacturing defects such as misalignments that result in high levels of pollution generated, energy consumed, and excessive wear on riveting and welding tools that are not only expensive to replace but also risk loss of production capability. Heavy vehicle manufacturing creates special challenges in terms of sustainability. These vehicles are almost iconic in the most damaging aspects of contemporary urban living: levels of pollution that can cause severe ill health, greatly elevated levels of noise, and large amounts of road area leading to high levels of congestion and resultant long holdup times. Furthermore, commercial vehicle fatigue-tested parameters drive current structural integrity approaches to a much more conservative design envelope than is true when testing fatigue life at a constant amplitude. This conservatism leads to the use of more materials and more costly assembly that is essentially unnecessary. Such an over-designed vehicle not only contributes more to urban inefficiency but also has much greater environmental costs during the vehicle's life. Reducing the vehicle weight is one consideration, but weight is not the only, or even the most important, consideration. While reducing fuel consumption does not have a dominant effect on CO2 production in a small car driving on short rural highways, this production effect is the most prominent for heavy commercial vehicle designs undergoing long highway journeys. The resulting CO2 production is growing in recognition and is the most urgent design goal if the automotive industry is to make a significant contribution to the goals presented in PLANET 2050. Reducing the vehicle weight, up to a limit called 'minimum floor design weight' that can be defined as the weight at which the gross weight of the vehicle is equal to the weight due to payload and structural weight, is much more relevant to estimations based on EU-ETS targets. Since CO2 is generally a surrogate for fuel consumption during overall urban operation, fuel operation is not at a limit when a constant ideal range is defined.

4. Big Data Analytics for Sustainable Heavy Vehicle Manufacturing

Incremental regulatory demands are challenging the sustainability of heavy vehicle manufacturing. Barring significant changes in national freight policy, the economic and safety contribution of heavy vehicles will continue to overshadow automotive production. Regulatory barriers preclude simply offloading the task to light vehicles or commercial materials. The realization of smart production with Industry 4.0 solutions is also constrained by vehicle type and customer production volume. The industry is also challenged by the aging of the heavy vehicle customer fleet, which creates a long-range demand for legacy vehicles, legacy tooling, and legacy production methods.

Despite its regulatory barriers and constrained production transition due to the aging customer vehicle fleet, the heavy vehicle industry could still advance manufacturing sustainability and maintain profitability through big data analytics that capitalizes on the vast messaging capacity embedded in today's and future vehicles. The vehicle industry consists of smart manufacturing platforms that alter the relationship between the manufacturer, the user, and the vehicle. In addition to driving Class 9 trucks, last-mile delivery trucks, long-haul transportation of goods, smart agriculture, smart mining, construction, and other market segments, these platforms provide valuable situational information that could be transformed into actionable business intelligence through effective engineering sciences. Relationships create a circular economy when the user wishes to upgrade, retire, or dispose of the vehicle. This chapter broadly outlines the possible sustainability opportunities in heavy vehicle manufacturing and repairs utilizing embedded big data analytics in the vehicle platform and provides key logistical drivers and challenges as implementation challenges.

4.1. Challenges and Opportunities

The existing and upcoming trends in the automotive industry exhibit a landscape of complex systems. These systems can be seen as multiple large structured systems that encompass both vehicle manufacturing and cityscapes where transportation trends are influenced. Disparities and polarized developments are inevitable because of continuous transformations, such as environmentally friendly vehicles and urban transformation. Thus, the trend and the profile of economies and societies that emerge from this transformation, driven by high expectations for a sustainable environment, extended lives of the users, and the reduced need for ownership of a large number of goods, particularly vehicles, is a challenging one. One of the preliminary objectives of an automotive company is to maintain profitability but at the same time respond to the needs of society willing to pay for both attributes: the services required and environmental sustainability. Other attributes, such as safety and security, also need to be fulfilled. Since these attributes are established and regulated by public authorities and international bodies through various standards and regulations, the balance between the quantitative criteria and pragmatic safety and durability indicators that define the performance of a vehicle is kept under continuous surveillance. The societal, economic, and technological aspects require the automotive industry to make, with wisdom and careful consideration, the transformation toward integrated mega cities where dissimilarity and divergence may never be eliminated but have to be managed.

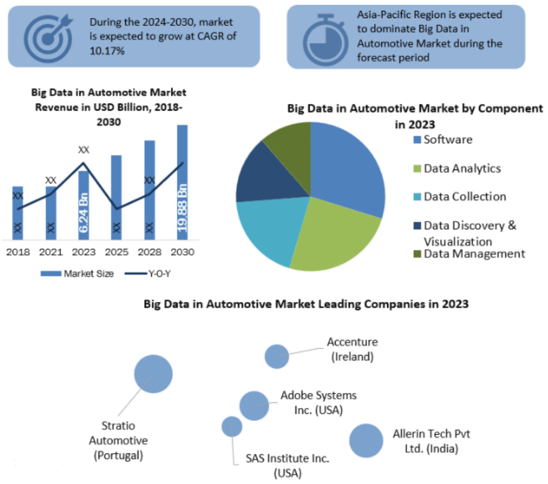


Fig 4 : Big Data in Automotive Market

4.2. Case Studies and Best Practices

An increasing number of manufacturing organizations support the view that process and production data should be analyzed to extract business value and transform it into decisions and actions serving business needs. The current practice and experiences of data usage present a complex picture with a variety of projects, technologies, and cultures. Different levels of readiness, maturity, and willingness to invest in data analytics make up this dynamic field. The utilization of manufacturing data for analyzing and improving manufacturing processes has become a hot area of research, and there has been an emergence of great interest in different approaches among both researchers and industrialists. It provides an opportunity to discover hidden information in the form of knowledge that can help improve manufacturing processes and increase profitability. In this section, we present and discuss two currently conducted big data analytics projects.

For every heavy vehicle assembly to customer order, a large number of variables are known, along with continuous data collection. Most data is unidirectional, but with the aimed capability to include more sensory and automated data collection, the potential is large. The prediction of the mechanical stability of assembled products, produced against tight tolerances, leverages the potential to improve vehicle quality, cost, and production efficiency. However, no explicit theory-based model has been found to correctly describe the relationship between assembly features and the desired mechanical stability. In this work, machine learning has been employed to investigate the complexity of the prediction task. Data has been collected, models designed and validated, and tested on new production and development data of interest. Data visualization has played a key role in identifying data subsets that have provided qualitative results, indicating promising outcomes of prior knowledge learning and intelligent model capacity.

Equation 3: Emissions Calculation
To track carbon emissions:

$$\text{Total Emissions}(TE) = \sum_{i=1}^{n} (\text{Emission Factor}_i \times \text{Activity Level}_i)$$

Where:
Emission Factor = CO_2 emissions per unit of activity (e.g., kg CO_2 per kWh)
Activity Level = Amount of energy or material consumed

5. Conclusion

Based on a review of the application of big data analytics in the context of a specific industry - heavy vehicle manufacturing - this paper develops a forward-looking plan for analyzing large-scale data sets and integrating results that would support the automotive industry's aspirations of providing personal mobility for people around the world, and doing so within the boundaries of a planet growing from nine to perhaps more than 10 billion people by the mid-century. The framework connects the goals of sustainability with the detailed objectives and quantitative targets of an industry framework and offers measures implemented through virtual product development, manufacturing, and end-of-production life. The framework depends upon customer demand as the initial trigger for using big data to collect customer-driven information. Several specific conclusions can be reached by using data analytics to achieve goals in heavy vehicle manufacturing. Many heavy automotive manufacturers have been involved in research that could be useful for a shift to customer-driven big data collection with results used for virtual product development and redesign to improve recyclability. First, stakeholders must communicate the message that a "win-win" is concerned with improving the environmental performance for customers and other stakeholders while reducing costs is the primary goal of the shift to customer-driven data collection for improved sustainability. Second, the use of big data is not fully implemented due to prior method problems that depart significantly from the basic assumptions of predictive regression. Major requirements are staff and organizational capabilities for managing and robust algorithms for storage, retrieval, and analysis in lead time according to the VMU and the OEM. Third, the paper identifies at least two areas for immediate near-term research funding for critical technical challenges. Incomplete sub-objectives are in effect on the road to 2050 and also indicate future pricing for substitution.

5.1. Key Findings and Recommendations

The combination of data analytics and advanced manufacturing technologies becomes important for heavy vehicle manufacturers to ensure economic growth, environmental care, and quality of products. Given the plethora of benefits that could be harnessed, the formidable challenge remains the development of data analytics-driven platforms that enable manufacturers to extract data and make more informed decisions in real-time, and also enable them to gain more perspective on data from complex manufacturing processes. In developing the platform, it is important to incorporate analytical models and tools that can seamlessly integrate with the manufacturer's data to model, simulate, and analyze the manufacturing processes. The lack of such data-driven tools can put the manufacturers in a situation where they infuse complexity into technical and solution architectures, and in turn, compromise their goals of simplification and standardization.

We develop a data analytics platform prototype that 1) captures data from three heavy vehicle manufacturing processes, which are: cab trim line, engine evaporator assembly line, and bus battery EV test line; 2) utilizes several statistical and machine learning models for the analysis of the data and the report generation; and ultimately 3) showcases the graphic user interface of the system alongside explanations on how the data can be used for operational improvements. The prototype integrates heterogeneous data at high speed to provide real-time data to various stakeholders in the manufacturing process, who benefit from tools that give them immediate access to information necessary to understand why products fail, quality reports, and performance management dashboards. Our prototype and the sample results show proof of concept for developing a data-driven visualization platform that supports decision-making by operational staff, top managers, and data scientists when utilized to improve quality and operational performance.

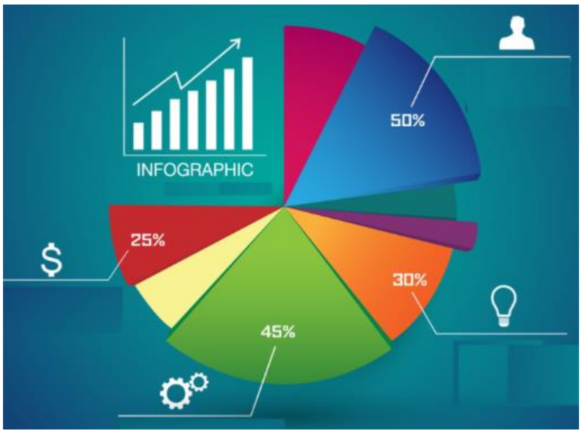


Fig 5: Global Big Data Analytics in Automotive Market 2030

5.2. Future Trends

The combination of 5G infrastructure and connected networks will enable heavy vehicle engines to continuously analyze transportation conditions and vehicle operation conditions, identifying chances of safe operation in low-stress areas. This will dramatically reduce insurance and operating costs. The continued development of component materials that account for 60-70% of vehicle weight will continue to reduce the weight of heavy vehicles. Emerging digital logistics is changing freight transport and the business model of manufacturers. On-demand manufacturing methods minimize inventory costs. The design and implementation of high-quality data collection engines to meet requirements, and their effective use in decision-making, production operations, supply chain designs, transformation process designs, and some business processes, can be close to species and differentiators. By using big data, manufacturers can develop data-driven management practices, and intelligent data sensors can provide insights based on advanced analytics.

In the future, data, modeling, simulation, and advanced analytics will come together. Closing the loop of end-to-end analytics with leading automotive manufacturers will reduce the difference between high-resolution data now visible in some parts of their value chain and accurate demand predictions. Better design responsive distributed energy systems suitable for distributed electricity demand and generation of electrified vehicles. The pursued goals include system resilience, defined as safety without utility access and robust provision of survival conditions in unexpected disasters. These energy systems precede existing high-quality power electronics, solar photovoltaics, electric vehicles, vehicle-to-grid systems, microgrids, and vehicle aftermarket, as well as politics. Automakers can pursue incentives and partnerships to develop responsive distributed energy systems to hedge against uncertain electricity supply conditions and reduce dependence on single plants during normal business operations. These initiatives will provide partners with a more reliable and profitable certified collaboration.

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