Migration Letters

Volume: 19, No: 6 (2022), pp. 1078-1090

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Integrating Predictive Analytics Into Manufacturing Finance: A Case Study On Cost Control And Zero-Carbon Goals In Automotive Production

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Abstract

Planning of future costs is essential to any organization, especially those committed to a zero-carbon future. This case study describes the development of a joint-level cost predictive analytics model in support of carbon footprint reduction goals. Realistically complex predictive analytics research using Enterprise Resource Planning data and machine learning in a large-scale multinational automotive company is presented, and the challenges of extracting generalizable conclusions to the industry at large from the context of a particular company are discussed. We aim to illuminate the benefits deriving both from collaboration between the finance and operational teams and from breaking the cost objects down to the level of component sub-complexing typically used by manufacturing engineers undertaking product cost estimation studies. The model was found to uncover cost reduction opportunities relating to assembly lines in the case studies designed jointly by manufacturing [1]engineers acting as domain experts. The work has direct implications for predictive analytics research related to sustainability goals, and, in particular, the ambitious zero-carbon goals in many smart manufacturing industries.

Keywords: *Cost Assessment; Cost Classification; Energy Cost; Emissions Cost; Predictive Analytics; Classification Task; Data Preprocessing; Machine Learning Model; K-Fold Cross-Validation.*

1. Introduction

The importance of finance for manufacturing strategy has increased over the past decades, due to the large capital needs and the increasing technological and environmental complexity of production investments. On the one hand, manufacturing executives strive for real-time financials to guide the implementation of their strategies. On the other hand, domain knowledge is important to validate the relevance of big data models for industrial applications. We perform a two-stage pilot case study to analyze if performance indicators from the accounting system can improve the prediction of future departmental costs. Real data is used for six months with no intervention. Our predictive models regionally reduce the mean squared prediction errors. When focusing on department cost outliers and gender differences, the accounting system's quantitative and qualitative data becomes more informative for the company's management

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control decisions. Accurate decisions guide the implementation of sustainable practices for a company that has set zero-carbon operations goals by 2040. To harness the potential of predictive analytics to improve managerial decision quality over time, we summarize the benefits of a dynamic predictive model in a proof-of-concept discussion.
Finance for manufacturing strategy is a recent and increasingly important theme in academic research. Next to decreasing tax liabilities of embedded intellectual property at domestic locations, executives might be better positioned for location decisions if they know how making strategic choices will lead to bottom-line profits and cash flow. On the academic side, empirical studies typically test or relate the importance of one or a few selected accounting ratios on basic financial performance indicators over time. In contrast to this view, some influential authors have argued that prior research has failed in turning operational decisions into consequences for long-term performance.

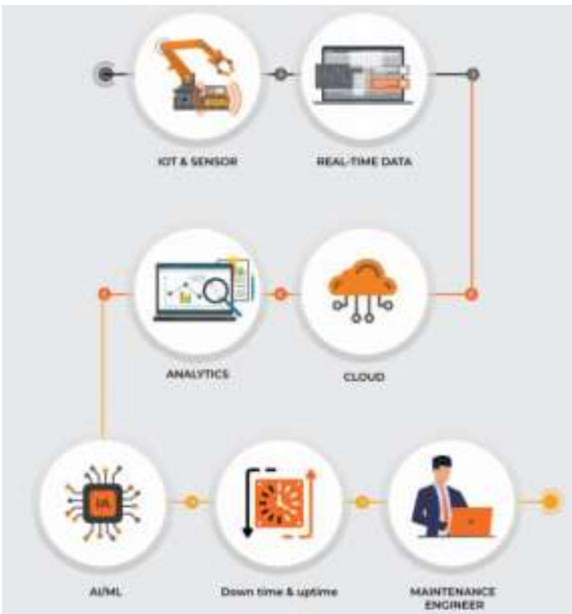

Fig 1: Predictive Analytics in Manufacturing

1.1. Background and Rationale

Besides consumer packaged goods and retail, automotive and transport is another top industry in sustainability. To mitigate their environmental impact, original equipment manufacturers are working with suppliers to meet their aggressive and challenging zero-carbon goals in manufacturing. Among various types of data analytics, predictive analytics can help the finance team with tools to do tactical and committed cost control. Having a finance team able to make manufacturing 4.0 feasible can be a useful competitive differentiator. However, suppliers are typically under cost pressure from OEMs and are finding it hard to allocate resources to the tool development that is necessary for implementing predictive analytics. To engage suppliers in integrating predictive analytics, we use a specific finance scenario as an example to show how the technology can help finance professionals in manufacturing with their most critical tasks.

1.2. Research Objectives and Scope

This study introduces accounting principles into predictive analytics to address the complexity and subjectivity of cost accounting, as well as to create transparency and comprehensibility for non-experts. It focuses on the mapping of detailed data from large production facilities to managerial and financial accounting in manufacturing companies. We propose a method to analyze and predict cost and profit margins at the production process level by combining the fundamentals of accounting associated with production systems with correlations derived from business intelligence and big data environments. Our approach takes into account perturbations in data quality caused during big data processing. We also recognize complex production system data dependencies and recipes and use transcriptions to structure billions of multi-dimensional time series data points. The main objectives are as follows: We aim to understand and describe the challenges and conditions necessary for the implementation of cost accounting integrating data mining and predictive analytics. We then describe the scope of both managerial and financial accounting and afterwards, propose discrete analytical steps for engineering data integration. To discuss the commonalities and differences in relevant approaches, a cross-functional comparison with academia, as well as consultancy studies, has also been carried out. Data perturbations and pre-processing involving data obfuscation and encoding complete the discussion. The study is validated on use cases in large automotive production facilities and a lawnmower manufacturing process. At the end of the fieldwork, the contribution of this research is reviewed in a discussion. The text ends with a conclusion and an outlook.This study innovatively integrates accounting principles into predictive analytics to enhance the understanding and transparency of cost accounting in manufacturing settings. By mapping extensive production facility data to both managerial and financial accounting frameworks, the research addresses the complexities and subjectivities inherent in cost analysis. The proposed method combines core accounting fundamentals with insights from business intelligence and big data, enabling detailed analysis and prediction of cost and profit margins at the production process level. It also accounts for data quality issues arising during big data processing and navigates the intricate dependencies within production system data. Through a rigorous cross-functional comparison with academic and consultancy approaches, the study outlines the necessary conditions for implementing integrated cost accounting and presents discrete analytical steps for effective data integration. Validated through real-world applications in automotive and lawnmower manufacturing, the findings underscore the study's contributions to enhancing decision-making in production environments, ultimately concluding with a reflection on its implications and future directions.

Equ 1: Cobb-Douglas production function and costs minimization problem

$$\frac{\partial Y}{\partial L} = A\alpha L^{\alpha-1}K^{\beta}$$

$$\frac{\partial Y}{\partial L} = \alpha A L^{\alpha} L^{-1} K^{\beta}$$

$$\frac{\partial Y}{\partial L} = \frac{\alpha A L^{\alpha} K^{\beta}}{L}$$

2. Literature Review

In the fast-developing area of productivity and decision-making sciences, financial modeling for overall operational performance has been connected mainly to accounting and management control, and to data science that has emerged as an extension and a complement to these tools. An array of decision-making tools has defined the modeling process in business processes, leading to a wide variety of methods such as simulation, business process management, data mining, and others, and methods combining financial and non-financial objectives. A large number of accounting and finance studies have delved into process and product life-cycle costing, yet they have concentrated mostly on cost accounting and management control from the point of view of advanced cost technique applications that cannot necessarily guarantee better financial performance.

Decisions on purposeful allocation of capital and cost budget planning in business processes focused particularly on investment and operational activities from the financial and business strategy point of view, are to a certain extent still left "hunch-based." In services and manufacturing, we report a lack of studies that use certified methods of finance such as terms from financial ratio and accounting technology theory, present financial modeling knowledge, and apply data that comprises both information from financial statements and process performance. The present study addresses this gap. In doing so, it capitalizes on advancements in the management control, decision-making, and predictive analytics interconnected areas.

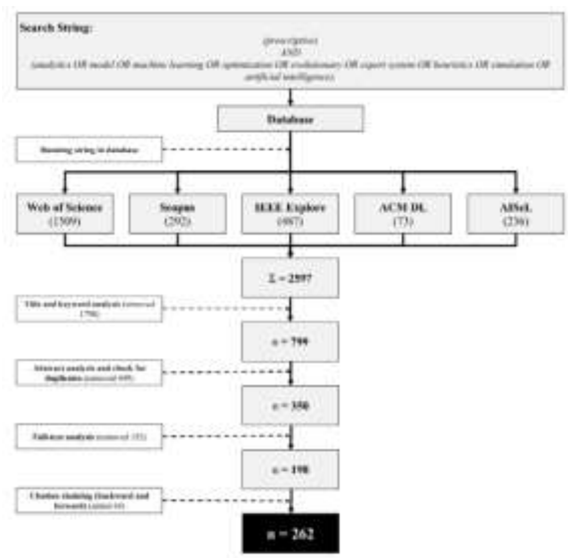

Fig 2 : Literature Review

2.1. Predictive Analytics in Manufacturing Finance

With its data and forecasting orientation, predictive analytics is often seen as a special form of business intelligence. It tries to enable better decisions when actions are taken based on the prediction of probabilities. Predictive analytics uses time series analysis, data mining, decision trees, and market-based forecasting. It includes many activities, from data preparation, data mining, and data analysis, to implementation and validation. In addition, a good variety of these activities happens simultaneously and continuously in any business problem requiring predictive analysis.

Data mining is defined as the application of methods to discover patterns in data. Data mining is used frequently in business forecasting with statistical and analytic methods. Ultimately, it is for value enhancement. Advanced data mining techniques can be powerful for helping businesses conduct better business decisions. They provide increased automation, support more data sources, and handle more unstructured documents such as emails, executing a wide range of analytics. Predictive analytics combines machine learning techniques, data analytics, and predictive modeling to identify problems and recognize patterns and anomalies to predict future developments. It delivers information to improve decision-making, facilitate reporting, and contribute to financially sustainable, top-quartile performance. Predictive analytics and machine learning understand strength in numbers and use multiple algorithms and guesses based on different datasets, layering the parameters of these models in a deep, complex web. The costs of these models do not suffer from the complexity of self-destructing when more examples of the input are added, versus what you'll find with simple, classic statistical models.

2.2. Cost Control and Zero-Carbon Goals in Automotive Production

Although our paper is more focused on predictive enterprise finance, knowledge of a specific enterprise environment constitutes part of the data landscape definition in ESA. In this section, we offer an example of domain-specific supply chains and production conditions, discussing two topics, namely cost control and carbon footprint calculation. Zero-carbon commitments require a carbon footprint of almost zero. The billions of cars manufactured in the past one hundred years, with only minor maintenance or end-of-life recycling, present a substantial challenge in themselves. A working group has defined the following decision logic for companies to follow over the next decades, departing from business-as-usual business cases.

The carbon footprint must be significantly reduced from the early production stages, not only from the end of the lifecycle of the car itself. Manufacturers need to be able to identify reduction opportunities from the multiple configurations being produced every day. Deriving the carbon footprint and consumption of a potential future car from a drawing demands a significant amount of detail and work that is not always typical of supported production systems. During the first developmental stage, a manufacturer has to agree to carve out the zero-carbon concept for these use cases, focusing on modeling production systems and providing instant results for incurred costs at each step. A predictive analytics product for time-series data makes this possible.In the context of predictive enterprise finance, addressing the carbon footprint from the outset of production is critical for automotive manufacturers aiming to meet zero-carbon commitments. Traditional practices often focus on emissions at the end of a vehicle's lifecycle, neglecting the significant impact of earlier production stages. To effectively reduce the carbon footprint, manufacturers must identify opportunities across various configurations produced daily. This requires a detailed analysis that goes beyond conventional production systems, leveraging advanced modeling techniques to forecast emissions and costs from initial design phases. By implementing a predictive analytics solution that analyzes time-series data, manufacturers can gain real-time insights into the carbon implications of their production choices, allowing for informed decision-making and a strategic pivot toward sustainable practices. This approach not only enhances cost control but also supports a transition to a more environmentally responsible automotive industry.

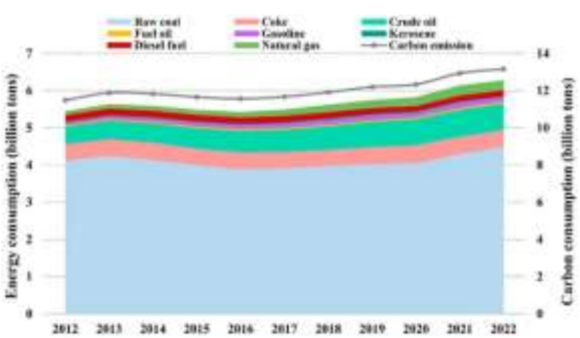

Fig : Carbon Emissions

3. Methodology

To quantify the management costs, a machine learning-based predictive tool was used. This model can estimate the life expectancies of the induction hardening equipment used during car production. The IH device and inspection data have been used in this study. These time-stamped data exist in the company's process data storage, but some of it could be damaged, there could be variations in the format, and the data might not be queryable. For a sample of the data, inspection and equipment usage data were combined with the unique equipment IDs using a command. Such inquiries involved selecting specific equipment, counting the number of induction or quenching processes in the given time frame, evaluating the faults, and counting the inspections for a specific time frame. Then, text files of this data were prepared. This data set was read and filtered in the environment with specified libraries for such operations.
Our analyses aim to address a real-life problem in automotive production. We employed several predictive algorithms with different preprocessing and feature selection techniques to identify the most effective and feasible method. We compared asset-specific lifetimes with other factors such as production parameters and maintenance activities in a data-driven approach to provide more accurate life expectancies during production. The analyses succeeded in terms of predictions, even if the outcomes were ranked by machine learning as less successful. To the best of our knowledge, no separate method has been developed at institutions for predicting the remaining usage period of induction hardening devices.

Equ 2: Single-objective optimization regarding lifecycle GHG emissions reduction

$$\mathrm{GHG}_{\mathrm{CCU}} = \sum_{i}\sum_{r}\alpha_r \cdot F_{i,r} + \sum_{i}\sum_{u}\alpha_u \cdot U_{i,u} + \sum_{i} F_{i,\mathrm{CO}_2}$$

$$\mathrm{GHG} = \alpha_{\mathrm{NGCC}} \cdot E_{\mathrm{electricity}} + \sum_{i}\sum_{p}\alpha_p \cdot F_{i,p}$$

$$\mathrm{GHG}_{\mathrm{reduction}} = 1 - \frac{\mathrm{GHG}_{\mathrm{CCU}}}{\mathrm{GHG}_{\mathrm{ref}}}$$

3.1. Data Collection and Analysis

In this section, we perform cost control based on predictive analytics methods. Data used to construct the predictive model are collected from an automotive manufacturing company. In our study, we only have access to the available public data related to workforce cost, including both labor hours and labor costs, as well as cumulative production time and vehicle data that represent vehicle models and options in the production process. It is usually difficult to collect other cost information related to energy consumption or external resources, such as utilities, scrap costs, and general support costs during the manufacturing process because some essential data are confidential. In addition, the processing of detailed cost data from a certain production process shows multinational complexity. There is an increasing number of cooperating automobile manufacturers, suppliers, and logistics companies in global vehicle production networks. There is also a lot of cross-research on production cost and vehicle manufacturing complexity.
A set of analytical methods is used to fully utilize this public data. Because of this and some critical data that are not available, which truly represent the intelligent part of manufacturing finance in predictive analytics, we aim to increase the intelligence behind the decision and

control rules. For the case study, we separate the output of the production-cost model into fixed cost, labor cost, external cost, and energy cost. In other words, we decompose the overall cost of the production process modeled under traditional methods into these categories and then calculate labor costs for respective vehicles, all for each period. The performance of the proposed model is then evaluated by comparing these results with those obtained using a traditional approach. The traditional method, though applied in the majority of companies, is usually based on industry experience and the fulfillment of certain roles—in this case, historical participation in finance.

Fig 3: Data collection and Analytics In Manufacturing

3.2. Predictive Analytics Techniques

The Predictive Analytics Portfolio (PAP) encompasses many different techniques to uncover predictive patterns in large and complex datasets. The selection of the specific techniques must be based on a business-oriented understanding of the question. This paper focuses on three of the most relevant forecasting techniques that integrate well to describe relevant questions of cost control in production systems because each technique points out different dimensions of the challenges that arise in these systems: time-series forecasting, survival analysis to identify processes that dampen out or fertility rates of organizational capacities, and text mining. These techniques are complemented by qualitative interview data as well as structured focus groups of floor-level workers, planning staff, and management. Data will be interpreted with a particular focus on applying insights to cost control questions and zero-carbon production systems.

Many interesting papers and reviews of predictive analytics techniques have been published during the past five years. Very few of these papers, however, systematically address questions that are important for a management accounting audience. Various studies have analyzed predictive analytics techniques to improve enterprise performance. The technical predictive analytics techniques are, however, rarely aligned with economy-centered questions. We will now briefly introduce three techniques. This covers the scope and limitations of the technical results that have been reported here and elsewhere and, at the same time, explains the motivation of our study. These explanations should make clear to the reader why we study time-series forecasting and survival-data techniques, and what kind of literature and practical experiences our approach encompasses.

4. Case Study: Implementing Predictive Analytics in Automotive Production

Automotive finance professionals understand the value of analyzing both external and internal business data to better predict future costs of completed vehicles. Predictive analytics technology is no longer viewed as a crystal ball that produces game-changing forecasts about what the future holds for automotive organizations. As automotive manufacturing technology goes increasingly digital, timely use of robust operational performance data is an essential component of the finance professional's toolbox. Production process visibility can be utilized to complement existing internal data with benchmarking information. Finance professionals

can either work with cross-disciplinary teams and internal shared service centers or establish their predictive analytics capabilities. A finance professional's digital transformation journey requires a mindset shift to focus on leveraging data for proactive and strategic insight.
We present a specific case study from a European automotive manufacturer that has set the goal of reducing production costs and emissions to achieve economically sound zero-carbon balance sheet targets. They intend to digitally control their emissions via pilot projects fostering production sustainability. To achieve this goal, the team is integrating digital transformation into the management value chain model. By integrating technologies in a predictive analytics architecture, finance executives will discover several digital ecological control towers. These predictive controllers are designed to enhance organizational learning and agile problem-solving capability. The paper shows how finance professionals can re-engineer vehicle, production, and management dashboards to facilitate plant observation and root cause identification, correlating the impacts of energy scarcity and component complexity.

Fig 4 : Manufacturing Use cases

5. Results and Discussion

As was shown in the case study, predictive analytics offers new possibilities for the risk prediction of unfavorable variations in production costs by considering historical financial data together with operative technical data, simulating and monitoring the effects of financial measures on manufacturing and its costs and considering sustainability objectives. This answers part of the current call to consider more broadly the impacts of plasticity in manufacturing. The natural next steps would be to expand the model integration side by including financial option theory and the value of flexibility, not only when making capacity or process investments, but also concerning production output decisions based on actual market demand and price elasticity. However, research has shown that the consideration of sustainability-related carbon costs in output operations is important, as they impact the production investment and finance decision in the first place, and failure to adequately anticipate carbon costs can lead to large sunk costs.
Another direction would investigate the whole series production and order fulfillment process by assessing the financial risk of order delays due to production bottlenecks, acting upon the production system design, or flexibly changing the manufacturing strategy if order delays are anticipated but the customer cannot or does not wish to wait. Research showed the importance of the change in decision structure in decentralized manufacturing tactical planning when aligning production and warehouse strategies for sustainable supply chain operations. These naturally align with the broader interest of considering the customer in more depth when alignment between sustainable operations and the sustainable product portfolio is considered. The customer is central to all manufacturing activities, and flexible manufacturing investment and finance decisions help to better align customer preferences and wants with product portfolio contents. Further enriching the currently purely internal focus, future research should

also substantively consider external financial markets. For example, the study touches upon the basic problem of comparing maintenance service contracts and considering the duration of the cornerstone raw material supply. These are all directed at accounting in more detail for contracts in the financial constraint equations during each manufacturing phase. For a more commercial perspective, the research could also include container shipping and focus on the interaction between inventory and production decisions when clearing and setting the expected income generated at the intermediate stage.

Equ 3: Cost minimization with a Cobb-Douglas function — Micro Economy

$$w_1 = \lambda \alpha x_1^{\alpha-1} x_2^{1-\alpha}$$

$$w_2 = \lambda x_1^{\alpha-1} (1-\alpha) x_2^{-\alpha}$$

5.1. Cost Control Outcomes

The outcomes show that the Year-over-Year Growth (YoY) of the production cost was planned to increase by 5 percent per year while the automotive business wanted to achieve a closeness to zero desired outcome as the receipt of the total costs is borne by corporate targets of revenue, resource usage, quality, and technology. The optimized pattern of the corporate targets could ensure work towards an innovation-friendly environment. These financial engineers could provide valuable insights into engineering cost control as they have learned to reduce the vehicle production cost with steps of material, logistics, labor, energy, and efficiency. With predictive analytics, due to the quality disturbance propagation towards the quality control areas, the cumulative business loss could be warned rapidly. This application benefits from the quality control system being designed for automotive manufacturing with so-called "door-to-door," "from-cradle-to-grave," and third-tier quality control systems. For the third-tier quality control, such activities will be automatically executed in several stages to generate the patterns of the pre-rated low-cost warning for the undesirable ongoing trends. In other words, these stage models could work as the production capacity, so the financial engineers could allocate "contingency decrement" against "contingency production loss" in the desired ratio. As "never-be-jobless," the cost engineers would like to terminate "on-the-job training" of automotive production and move towards the right "knowledge alignment." In such cases, they learned that their practice patterns could ensure the incremental machine intelligence predicted and discovered financial streamlining and cost optimization by analytic insights. If these were the holistic effects of employing lean predictive analytics as the baseline for financial engineers or organizations in vehicle production, YoY could determine these community/profit center organizations and FPP could offer financial support for other emerging startup companies.

5.2. Zero-Carbon Goals Achievement

Machines in the final section of a production line are power consumers, as almost 50% of emissions belong to this section, although the section occupies the smallest area in the assembled lines. Energy losses are directly proportional to the burners. For example, due to an air gap, the paint thickness becomes different. Unlike the other sections, each color will have an oven and the corresponding tray. Any mistake in the ordering process may cause paint thickness differences. In this case, the trays will be brought closer to the burners, reducing the paint thickness. On the other hand, the burners' energy will increase, thereby consuming more energy. Moreover, the total color time will increase because the state of the panel is not

guaranteed. Since the panel can be painted again, different trays will correspond to the same panel.
To achieve zero-carbon goals in the concept of the manufacturing strategy of the company, all developed models in this study can be used for integration into a predictive maintenance system, which can prevent most of the cost waste that ineffective maintenance could not avoid. In addition to the maintenance functions of the models, they were also trained for environmental applications. They can be used for businesses and financial trainees to create or analyze a predictive performance matrix: 1) quality performance, 2) green performance, 3) financial safety performance, 4) cost control performance, 5) verification of financial reports, effective collaboration, etc. For the cost control and zero-emission goals, they have performed well in terms of operational performance and ongoing financial safety in realizing EMS. This is crucial for monitoring the process of production with a simultaneous decrease in power utilization.

Fig : Predictive Analytics in Manufacturing

6. Conclusion

The reported low adaptability and high initial and operation build-up cost of AI/machine learning (ML)-based MA on production control and manufacturing finance lead to the low applicability of currently circulated literature. This might deter opportunities for businesses to progress or for the future of manufacturing finance to take off. The multiple case studies, semi-structured interviews, and questionnaires conducted with the subject-matter experts of an automotive producer and their suppliers aim to address one of the above challenges. They convey knowledge related to the current state of AI/ML-based MA CI practices in automotive parts production, explore their enablers and inhibitors, and consider the financial PPS that could incentivize companies to progress in this domain. The limited company expenditure on AI/ML-based CI in automotive parts' production, with manufacturing finance supply focused more on PPS than on a total cost of implementation, needs supervisory scrutiny that focuses on 'how to', 'how much to', and 'how much it costs'. The insights in the reported pilot focused more on 'what' and 'why' than on 'how' action is required. A potential point of sectoral interest is that the input cost of the financial PPS provided to the suppliers is the condition for achieving a customer's zero-carbon goal in auto parts production.

6.1. Future Trends

Presenting findings from the automotive industry and supply chain, cost structures, and the implications of existing industry benchmarks, as well as implications for future cost control and normative suggestions. Future trends in internal control, the trend toward services and platforms in future car production, and implications for automotive finance and related cost elements are outlined in the last section. The future trends of the automotive industry, such as services like car sharing, are reflected in global price benchmarks, including the original architecture of the first production network. In addition, the control of investment-related machine and building costs in the area of car parts storage, with clear guidelines for future investments, is also significant. Outlook and future trends: The automotive industry is facing radical technological and market changes with strategic implications – especially in automotive manufacturing and its related organizational structures and cost elements. The number of automotive business models and product portfolios has multiplied with new electric vehicle manufacturers and suppliers. Vehicle production alone cannot generate such major additional revenue contributions to universal profitable growth. From a macroeconomic viewpoint, the currently strong growth of vehicles and vehicle parts in production chains extends beyond simple local tax base and employment effects. The company established its internal sales department. We therefore do not want to miss contributing to greenhouse gas regulation and legislation.

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