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Predicting CO_2 Emissions in Circular Economy Transitions: A Bayesian Network Approach under Data Uncertainty

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Abstract

For the transition to a circular economy, an accurate assessment of CO_2 emissions from production processes is essential to make informed end-of-life decisions. Product passports and management shell models can fill these gaps but are currently at the very beginning of their introduction in industrial processes and are too comprehensive and data-intensive for widespread use across many components. To address this problem, we propose a Bayesian network model that predicts the CO_2 emissions of the production of a component and incomplete data. It combines information from metadata with concrete knowledge of process flows to provide statistically supported quantitative statements.

Keywords: Bayesian Network; Circular Economy; CO_2-prediction; End-of-Life-Decision;

1. Introduction

The necessity to make the economy more circular is driven by multiple factors. Economic factors include resilience against supply chain disruptions and potential cost savings through the reuse of already refined components. Ecological drivers involve reducing CO_2 emissions in producing high-quality components, especially those with high metal content. Political resilience is critical, as diminishing reliance on expansionist regimes prevents self-imposed limitations that could compromise the execution of sanctions.

This motivation gives rise to political and economic incentives to reduce CO_2 consumption in production. In particular, the decision for or against a particular remanufacturing strategy is closely linked to the expected CO_2 savings [1–3].

In order to specifically derive a remanufacturing strategy in the context of a defined CO_2 budget, the CO_2 balance incurred during the creation of the product must be known. However, it is currently not possible to determine the CO_2 emissions accumulated in a product during its production retrospectively. A commonly used static method for determining a CO_2 footprint is life cycle analysis (LCA). This approach seeks to derive a specific value for a given component or complex product by summing up the individual process steps throughout the entire production chain—a procedure that is both complex and time-consuming. On the one hand, the manual effort involved is great, and on the other hand, uncertain quantities such as the origin of a raw material for the specific product or the energy consumption of a specific machine cannot actually be determined, so that these analyses must remain limited to mass products such as simple consumer goods or products manufactured in extreme quantities such as smartphones. Conversely, model-based approaches exist for certain dedicated systems, but these are limited to only one specific process step in the context of a specific system and cannot be transferred to semi-finished products, for example [4,5]. To overcome the issue of unavailable data, Monte Carlo simulation is often used in LCA, offering the possibility to model uncertainties by repeating random sampling to approximate probability distributions and generating a wide

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range of potential scenarios [6]. This method helps quantify uncertainty in model predictions, though it does not inherently provide insights into causal relationships.

Digital twins and product passports are promising technologies for detailed lifecycle information but are not yet mature enough for dynamic CO_2 determination, especially with incomplete data.

In end-of-life decisions in the circular economy, evaluating these decisions requires considering technical, economic, ecological, legal, and societal aspects. [7] highlight the need for a holistic approach to evaluating these factors. [8] emphasize the complexity and dynamics at the end of the product lifecycle and call for an expanded view. A common challenge in end-of-life evaluations is uncertainty regarding quality and availability of used products as well as the costs of refurbished products [9,10]. Effective methods are needed to handle incomplete and inaccurate data to support decision-making in the circular economy. To optimize product life span, life cycle design and life cycle simulations are performed. The aim is to define the best product design for duration, see for instance [11,12]. However, these design decisions do not consider or calculate the CO_2 burdens incurred during production. Any values used are highly dependent on their accuracy, yet identical components produced at different times already exhibit different CO_2 footprints. For an effective optimisation of the product lifecycle, it is essential to have a suitable refurbishment strategy that takes consideres the CO_2 already expended during manufacturing.

Bayesian networks offer a promising approach to address these challenges. They model uncertainties and integrate expert knowledge, which is crucial in the circular economy, where complex decisions must often be made with limited data [13]. Bayesian networks allow known relationships to be mapped and provide robust insights despite incomplete data. By integrating Bayesian networks, statistical quantities such as production location share or regional energy mix distribution can be modeled. This approach can fill gaps in current methods and offer reliable decision support despite incomplete data [7,14].

In this work, we present a novel approach enabling accurate CO_2 balance prediction using Bayesian networks. Statistical variables like uncertainties regarding raw material origin, production timing, and site specifics are accounted for without exponentially increasing modeling effort.

2. State of the Art

Complex processes with conditional mutual dependencies can be modeled or represented in different ways. Historically, these different approaches have different roots and temporal dominance. In general, all methods can be categorized as either strictly deterministic-physical or heuristic-data-driven. Historically, differential equations and sometimes highly abstract and domain-related equation systems were used for physical modeling; their modern counterparts, using current IT skills, are complex simulation programs, usually using numerical methods. Classically, data-driven methods were understood to mean all statistical methods, in particular the derivation of statistically determined equation systems using design of experiments and the like. Recently, this area has been clearly understood by so-called AI methods as a form of machine learning.

Highly complex process chains with numerous steps cannot be practically described with classical methods. The physical modeling of all process steps to determine CO_2 resources would require extreme effort and detailed transient information, which is often unavailable, such as specific heating rates or axis accelerations of machines. Moreover, it is often impossible to deterministically map the exact production location and timing. A model-based representation through machine learning, such as Deep Learning with Convolutional Neural Networks (CNNs) or Large Language Models (LLMs), requires extensive historical data, which are not available for heterogeneous production processes. Even if data were available, the ratio between the total number of parts produced and the required data points makes successful training impractical. The interaction between the prediction quality and the necessary effort for data-based ML, physical modelling and using a probabilistic approach are depicted in **Figure 1**.

For ML-based modeling using deep learning, the necessary historical database of a heterogeneously distributed production

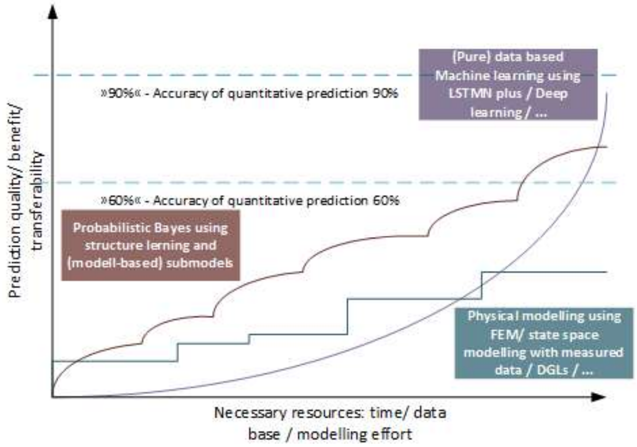

Figure 1: Display of the qualitative comparison of the utility value in terms of the quality of the statement on the carbon resources of a complex technical component depending on the time and data resource-related effort.

is not available in any way. Even if most of these were available, the relationship between the total number of parts or components manufactured, for example of a specific car model, and the number of data points to be taken into account in the heterogeneous process chains is such that successful training is impossible. This fact is often not given sufficient attention. In the area of AI-driven modeling, the focus would therefore have to be on the use of small, transferable building blocks such as certain sub-models for heating certain amounts of a specific alloy and their flexible linking to so-called hierarchical models using transfer learning.

Bayesian modeling offers numerous advantages for deriving quantitative models without claiming sub-percent accuracy:

- Modeling statistical quantities: Mapping statistical variables such as the share of a specific production location in the total volume or the distribution of the energy mix of a region for a specific year.
- Integration of known relationships and causal analysis: Bayesian networks can model known dependencies, such

as the sequence of steps in a process chain, without needing to teach them data driven.

- Handling incomplete data and uncertainty: They allow meaningful statements even with incomplete data sets. Bayesian methods can explicitly model uncertainties, providing a more robust analysis with imprecise or incomplete information [13,15].
- Causal analysis and modelling production processes: The production processes that are to be evaluated correspond to the directed and acyclic nature of bayesian networks, making it a good tool to model the processes. When the graph represents a causal structure it becomes a causal graph, allowing causal inference to quantify how changes in one variable cause changes in another [16].

Previous approaches to evaluating refurbishment procedures at end-of-life have highlighted the complexity and lack of holistic methods [6,17]. There is a need for standardized methods that can handle the dynamic and complex factors in EoL decisions, including the integration of sustainability aspects [18]. Integrating Bayesian networks into the evaluation of CO_2 emissions can address these challenges by providing a structured approach to modeling uncertainties and dependencies. This can improve the quality and transparency of decisions in the circular economy [19,20].

3. Method

To address the challenge of predicting CO_2 emissions under uncertain data conditions, we developed a Bayesian Network model tailored to the automotive body manufacturing process. The primary goal of this model is to enable informed end-of-life decisions in product refurbishment by providing insights into the CO_2 potential embedded within a product. Understanding this potential is crucial for determining how much additional CO_2 can be expended during refurbishment while staying within a defined CO_2 budget.

Our approach began with establishing a foundational model that captures the key variables influencing CO_2 emissions. We then expanded this model to include realistic scenarios by incorporating specific process steps from the automotive body manufacturing process, namely stamping, welding, painting, and assembly (**Figure 2**) as very general process clusters who will be further subdivided. By focusing on these four process steps, we aimed to conduct scenario comparisons and identify the major contributors to CO_2 emissions.

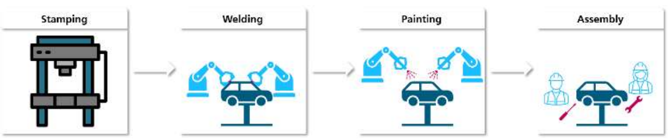

Figure 2: Automotive process flow for sheet metal parts

The Bayesian Network structure was carefully designed to model the dependencies between variables that significantly impact CO_2 emissions. The variables and their discrete categories are summarized in **Table 1.**

Table 1. Variables and discrete categories.

Variable	Categories
Production Year	1990, 2020
Production Location	Germany, Poland
Material	Steel, Aluminum
Plant Efficiency	1990: 1.0; 2020: 0.7
Season	Spring, Summer, Fall, Winter
Energy Mix	Renewable, Gas, Coal
CO_2 emission (per Process)	Low, Medium, High

Several key assumptions underpin our model. First, we assumed that older plants from 1990 have lower efficiency, represented by a factor of 1.0, while modern plants from 2020 have improved efficiency with a factor of 0.7, reflecting technological advancements over time. The energy mixes are initial rough assumptions, capturing general trends in energy usage over time and between locations. These assumptions are crucial for the model's initial validation and will be refined with more accurate data in future work.

Categorizations are used instead of continuous values to simplify the model and facilitate validation. By using discrete categories for variables like energy consumption and CO_2 emissions (low, medium, high), we can more readily compare scenarios and interpret the results, which is particularly useful in the initial stages of model development.

While our initial focus has been on testing the model against parameters with well-known influences—such as comparing the CO_2 emissions of steel versus aluminum, which differ significantly due to their respective energy consumption (10 kWh/kg for steel versus 58 kWh/kg for aluminum)—our primary research objective goes beyond mere validation. Specifically, we investigate whether integrating Bayesian network modeling with Monte Carlo simulation can effectively quantify uncertainties and clarify the causal relationships among production parameters in a circular economy context. In this preliminary study, our goal is to establish a robust foundational framework that reliably captures key drivers of emissions. Future work will enhance this model by incorporating probabilistic uncertainty (e.g., via beta distributions) and applying the approach to actual production process data, thereby providing more detailed causal insights for end-of-life and remanufacturing decision-making.

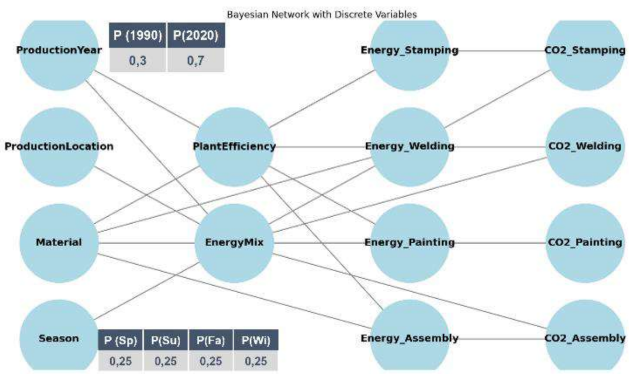

Figure 3: Display of the Bayesian Network with variables and interdependencies.

The Bayesian Network's structure models the dependencies between these variables and contains predefined conditional probabilities, as depicted in **Figure 3**. The production year influences both plant efficiency and energy mix, reflecting how technological progress and policy changes over time affect production processes and energy sources. The production location impacts the energy mix due to regional differences in energy availability and policies, and seasonal variations affect the energy mix by accounting for fluctuations in renewable energy generation.

Material and plant efficiency jointly influence the energy consumption for each process step, as different materials require varying amounts of energy for processing, and plant efficiency dictates how effectively this energy is utilized. The energy consumption and energy mix then determine the CO_2 emissions for each process step, with higher energy consumption and carbon-intensive energy sources leading to greater emissions.

To implement the model, we followed several key steps to ensure it accurately reflects the factors influencing CO_2 emissions in automotive body manufacturing. We began by defining the essential variables, which include production year (1990, 2020), production location (Germany, Poland), process steps (stamping, welding, painting, assembly), material (steel, aluminum), and plant efficiency. These variables are critical as they allow for the creation of various scenarios by combining different values, enabling us to analyze how each factor contributes to overall emissions.

Next, we collected and established values for each parameter based on realistic assumptions and industry data. Some values may still by synthetic, since the system is in proof-of-concept stage. The selection of these parameters and their dependencies reflects significant factors influencing CO_2 emissions. For instance, the energy mixes for different locations and years are rough estimates intended to capture general trends rather than precise values. This simplification is acceptable at this stage due to our focus on model validation.

We then expanded the model by adding new nodes to the Bayesian Network for each process step, plant efficiency, and material. The dependencies among these nodes were defined based on logical relationships:

- Production Year → Plant Efficiency: Technological advancements over time improve plant efficiency.
- Production Year & Production Location → Energy Mix: Energy policies and available resources vary by location and change over time.
- Material → Energy Consumption per Process Step: Different materials require different amounts of energy to process. Steel and aluminum energy consumption based on
- Plant Efficiency & Energy Consumption → CO_2 Emissions per Process Step: More efficient plants consume less energy, reducing emissions.

Energy Mix → CO_2 Emissions per Process Step: The carbon intensity of the energy sources affects emissions.

Although we initially considered implementing detailed probability distributions, we utilized a Monte Carlo simulation instead to derive the various states and assess uncertainties. This approach allows us to capture variability and uncertainty without overcomplicating the model at this validation stage.

We conducted sensitivity analyses by systematically varying input parameters to simulate different scenarios and calculating the CO_2 emissions for each combination. This analysis helped identify the variables with the greatest influence on emissions, such as material choice and plant efficiency. By analyzing the results, we identified key factors affecting CO_2 emissions and developed strategies for emission reduction. This process validated our model and demonstrated its usefulness as a decision-support tool in the context of the circular economy.

We employed a Monte Carlo simulation to assess the impact of uncertainties and variability in the model. The purpose was to generate a distribution of possible outcomes and quantify uncertainty in CO_2 emissions. We conducted 1,000 simulations per scenario, drawing samples from the defined probability distributions. The outputs included the mean and standard deviation of CO_2 emissions per process step and scenario.

Scenario comparisons are a significant advantage of using Bayesian Networks, as they allow for the analysis of different combinations of variables and their impact on CO_2 emissions. We defined eight scenarios by combining different values of production year, production location, and material. Comparing these scenarios helps in understanding how changes in key variables influence emissions and supports strategic decision-making.

We conducted sensitivity analyses to determine the influence of individual variables. By systematically varying key variables such as energy mix and material while keeping others constant, we quantified each variable's impact on CO_2 emissions.

Energy consumption values are crucial for calculating CO_2 emissions. In the code, energy consumption for each process step is calculated based on material, plant efficiency, and base consumption values. Higher energy consumption increases the likelihood that a process step falls into a higher CO_2 emission category (low, medium, high), directly affecting the overall emissions.

4. Findings

The results of our Monte Carlo simulation and subsequent analyses provide significant insights into the factors influencing CO_2 emissions in automotive body manufacturing. We present both the scenario comparison table (**Table 2**) and several figures that illustrate the key findings across different scenarios.

The Scenario Comparison Table effectively demonstrates how different combinations of variables impact CO_2 emissions. The choice of material is the most significant factor affecting CO_2 emissions. Aluminum production leads to significantly higher emissions compared to steel due to aluminum's higher specific energy consumption in processing—approximately 58 kWh/kg for aluminum versus 10 kWh/kg for steel [21]. Additionally, a CO_2 emission factor is applied on the materials which is derived of the energy mixes. For example, in 1990 in Germany, total emissions for aluminum are around 93.25 kg, while for steel, they are about 13.69 kg. These results highlight that material production emissions dominate the total CO_2 emissions, accounting for over 90% of the total in both cases.

Table 2: CO_2 Emissions Scenario Comparison (mean [$kgCO_2eq$])

Scenario	Stamping	Welding	Painting	Assembly	Total Emission
1990 Germany Steel	0.7591	1.6818	2.5500	0.6955	13.6864
1990 Germany Aluminum	0.7456	1.7719	2.9737	0.7632	93.2544
1990 Poland Steel	0.8235	1.7059	2.7794	0.8015	14.1103
1990 Poland Aluminum	0.7910	1.8507	2.8657	0.8209	93.3283
2020 Germany Steel	0.6068	1.3648	1.9470	0.5892	12.5078
2020 Germany Aluminum	0.6765	1.4253	2.0459	0.6495	91.7972
2020 Poland Steel	0.5886	1.2473	1.9950	0.5982	12.4291
2020 Poland Aluminum	0.6721	1.4152	2.1837	0.5884	91.8594

Emissions are slightly lower in 2020 compared to 1990 for both materials and locations, reflecting improvements in plant efficiency—from a factor of 1.0 in 1990 to 0.7 in 2020—and potential shifts in energy policies favoring cleaner energy sources. However, the reduction in total emissions is modest due to the dominance of material production emissions, which remain constant across years in this model.

Differences between Germany and Poland are less pronounced than those due to material or production year. In 1990, total emissions for steel are approximately 13.69 kg in Germany and 14.11 kg in Poland, while for aluminum, they are approximately 93.25 kg in Germany and 93.33 kg in Poland. This suggests that, under the current model and assumptions, the production location's impact on total emissions is less significant compared to material choice.

By examining the table, stakeholders can identify scenarios with the highest emissions—such as aluminum production in either country—and consider strategies to mitigate them, such as material substitution or investing in efficiency improvements. The table underscores the significant impact that material choice and technological advancements have on emissions.

To further illustrate the findings, we present several figures that illustrate the distribution and relationships of CO_2 emissions across different materials and process steps.

The boxplot in **Figure 4** illustrates the distribution of CO_2 emissions for different process steps (stamping, welding, painting, assembly) and materials (steel and aluminum). The boxes represent the median and interquartile range of emissions, highlighting variability and potential outliers. Emissions are consistently higher for aluminum across all process steps compared to steel, reflecting aluminum's higher energy requirements. Notably, the painting process for aluminum exhibits the highest emissions, indicating that this step is particularly energy-intensive for aluminum parts. The spread of the boxplots indicates variability in emissions, which could be due to factors such as differences in plant efficiency and energy mix.

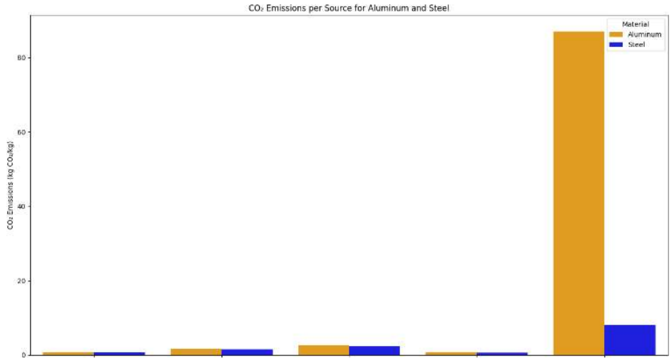

Figure 4: Barplot of CO2 emissions in comparison to material sourcing

The boxplot in **Figure 5** displays the absolute CO_2 emissions for various process steps and materials. Error bars represent the standard deviations, indicating the uncertainties or variability in the emissions due to factors like plant efficiency and energy mix. In this scenario, the bars for aluminum are substantially taller than those for steel in all four process steps, emphasizing aluminum's higher carbon footprint. The painting and welding steps contribute the most to process emissions, suggesting these processes are critical targets for emission reduction strategies.

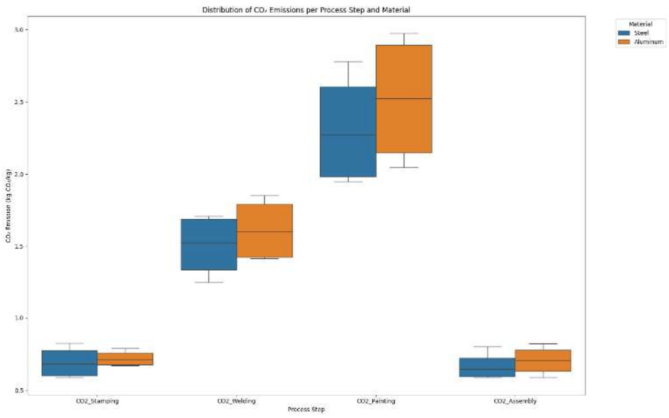

Figure 5: Boxplot of CO_2 Emissions per Process Step for Different Materials

The heatmap in **Figure 6** presents the correlations between CO_2 emissions of different production steps and the total CO_2 emissions. The analysis reveals low correlations between individual process emissions and the total emissions, indicating that material production is the primary contributor to total CO_2 emissions. This suggests that efforts to reduce emissions in this scenario must focus on material selection and sourcing materials with lower carbon footprints. Reducing emissions in individual process steps, while beneficial, will have a limited impact on the total emissions.

The combination of the scenario comparison table and the figures provides a comprehensive understanding of the factors influencing CO_2 emissions. The table quantifies the emissions across different scenarios, while the figures visualize the distribution, magnitude, and relationships of emissions across materials and process steps.

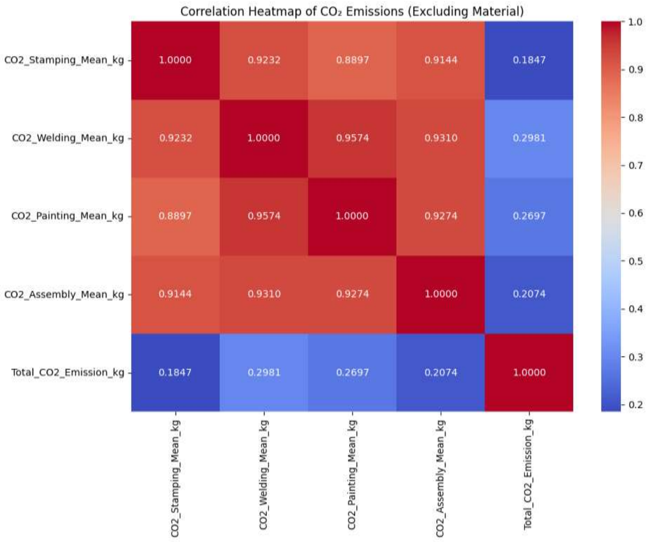

Figure 6: Heatmap of correlation between process steps and total emission

Our findings confirm that material choice and plant efficiency are the most influential factors affecting CO_2 emissions. Aluminum's higher energy requirements during material production led to substantially greater emissions compared to steel, emphasizing the impact of material selection on the environmental footprint. Technological advancements reflected in improved plant efficiency contribute to modest emission reductions in process emissions, showcasing the benefits of investing in modern, efficient production technologies. However, these improvements have a limited effect on total emissions due to the dominance of material production emissions.

While the energy mix has a comparatively smaller impact in our scenarios, significant shifts towards renewable energy sources could enhance emission reductions in process emissions. For example, if Poland were to adopt a cleaner energy mix, the emissions associated with production there could decrease slightly, highlighting the potential role of energy policy and infrastructure development in supporting sustainable manufacturing practices.

To demonstrate the additional utility of integrating causal inference into our framework, we performed an intervention analysis by setting the Energy Mix deterministically to 'Renewable.' Specifically, we modified the Bayesian network by removing the incoming edges to the EnergyMix node and replacing its CPD with a deterministic one, such that the probability of 'Renewable' becomes 100%. We then computed the expected CO_2 emissions for the process steps (Stamping, Welding, Painting, and Assembly) under this intervention using variable elimination. The results show the counterfactual estimates of process emissions when the energy source is fully renewable. This analysis highlights how targeted interventions in the energy mix can causally impact overall CO_2 emissions, providing decision-makers with valuable insights

Bayesian Networks facilitate scenario analysis by integrating various variables, their dependencies, and their probabilistic relationships into a coherent model. They enable the calculation of expected outcomes under different conditions and the assessment of uncertainties, supporting informed decision-making in complex systems. This capability is particularly valuable in evaluating "what-if" scenarios and understanding the potential impact of changes in production processes or policies.

5. Conclusion

Our Bayesian Network model successfully demonstrates the capability to predict CO_2 emissions under uncertain data conditions in automotive body manufacturing. The comprehensive approach, integrating specific process steps and accounting for key variables such as material choice, plant efficiency, and energy mix, enables informed end-of-life decisions in product refurbishment. By understanding the CO_2 potential embedded within a product, stakeholders can make strategic decisions on how much additional CO_2 can be expended during refurbishment while adhering to defined CO_2 budgets.

The Monte Carlo simulation and scenario comparison validate the model's accuracy and robustness. The findings highlight material choice and plant efficiency as the most significant factors influencing CO_2 emissions. Aluminum's higher energy requirements result in substantially greater emissions compared to steel, emphasizing the impact of material selection on the environmental footprint. Technological advancements reflected in improved plant efficiency contribute to notable emission reductions, showcasing the benefits of investing in modern, efficient production technologies.

While the energy mix has a comparatively smaller impact in our scenarios, significant shifts towards renewable energy sources could enhance emission reductions. This underscores the potential role of energy policy and infrastructure development in supporting sustainable manufacturing practices.

The successful validation of our model confirms its reliability and effectiveness as a decision-support tool. It allows for scenario analyses and "what-if" explorations, due to the use of causal inference, enabling stakeholders to assess the implications of changes in production conditions, material use, and technological advancements. The use of categorizations instead of continuous values simplifies the model and facilitates validation, but future work could involve refining the model by introducing continuous probability distributions, such as Gaussian densities, or the use of beta distributions. This would allow for more precise calculations and better integration of continuous data, improving the model's accuracy and predictive capabilities.

Expanding the model to include additional process steps and integrating real-world data would further enhance its comprehensiveness and applicability. By capturing a wider range of factors that influence CO_2 emissions, the model could provide deeper insights into the production process and identify more opportunities for emission reductions. The scope of the causal inference will also be expanded to get in-depth information about the changes within the respected processes.

In conclusion, our model offers valuable contributions to the field of sustainable manufacturing and the circular economy. It provides a systematic approach to evaluating CO_2 emissions under uncertain conditions, supports strategic decision-making, and highlights key areas for intervention. Future enhancements to the model will continue to improve its utility and impact, supporting efforts to reduce CO_2 emissions and promote sustainable practices in the manufacturing industry.

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