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Enhancing efficiency and environmental performance of laser-cutting machine tools: An explainable machine learning approach

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Abstract

This paper investigates the integration of sustainability and environmental performance in the development of machine tools. Through a literature review and a case study involving a fully automated solid-state laser-cutting machine tool, this research explores the potential of a data-driven, explainable machine learning (XML) approach to optimize machine tool operations for sustainability. Specifically, it addresses modeling resource consumption in laser-cutting machines, identifies the most significant factors influencing these models, and examines their contributions toward sustainable machine operation practices. Employing a combination of correlation analysis and stepwise linear regression for feature selection, and utilizing random forest regression models for predictive analysis, this study reveals that operational duration significantly impacts resource consumption levels, more than the effects of machine and laser configuration settings. The utilization of Shapely Additive Explanations (SHAP) further elucidates the predictive behaviors of these models, emphasizing the critical role of part contour length in program run duration and resource consumption. The findings suggest that optimizing machine speed and production planning, as well as incorporating part contour length as a sustainability Key Performance Indicator (KPI) during the design phase, can enhance the environmental performance of laser-cutting machines. Further, the analysis of resource consumption patterns of machine tools also offers actionable strategies to improve their sustainability during operation. It underscores the importance of integrating sustainability considerations into the development and operational phases of machine tools, contributing valuable insights to the field.

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1. Introduction

The integration of Industry 4.0 technologies, particularly laser-cutting systems, has significantly advanced manufacturing efficiency through high-precision and optimal utilization of material. However, these technologies also pose environmental challenges due to their high energy consumption and therefore emissions. In Germany, the industrial sector accounts for approx. 29% of total energy use in 2021, where machinery contributes significantly to CO2 emissions [1]. This underscores the need for sustainable manufacturing practices, especially in energy-intensive sectors like laser cutting. The European Corporate Sustainability Reporting Directive (CSRD) further emphasizes the need for transparent environmental impact reporting, pushing industries toward sustainable practice. Leveraging Industry 4.0's data analytics could optimize resource use and reduce environmental effects in manufacturing [2]. As a contribution, this research aims to align laser-cutting technology with environmental sustainability by minimizing resource consumption and

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enhancing operational efficiency. This is addressed by utilization of explainable machine learning (XML) techniques, which provide insights into the influences of different features on the prediction of the resource consumption.

2. Literature Review

2.1. Data-driven Sustainability in Product Generation Engineering

Complex mechatronic systems, are developed iteratively based on existing product generations, enabling systematic improvements through modification and recomposition of systems [3]. With the increasing degree of digitalization of mechatronic systems, an increasing amount of data is generated, providing the possibility to better understand the individual usage of the system in manufacturing facilities. Utilizing these field-gathered machine usage data, the system of objectives can be validated early in the product development process, resulting in a reduction of uncertainties by supporting decision-making based on data analysis results [4]. With such a data-driven approach, inefficiencies and areas for improvement can be identified to optimize the performance of new product generations [5]. Therefore, design modifications can be derived based on real-world performance metrics of the mechatronic system [6].

The CSRD [7] emphasizes the need for greater transparency in reporting sustainability. Therefore, integrating sustainability into the development of cyber-physical systems is crucial to meet the requirements of directives such as the CSRD. By using machine usage data gathered from the operation of existing manufacturing systems, new product generations of mechatronic systems can be designed more resource-efficient. Further, such data-driven approach in the development process of mechatronic systems not only helps companies comply with sustainability regulations but also offers a competitive edge by creating more sustainable products.

The emphasis on data-driven decision-making in the Product Generation Engineering aligns with global sustainability objectives by enabling the development of products that are more responsive to environmental requirements [8]. Through the strategic use of data, companies can ensure compliance with new regulations like the CSRD, while also driving innovations that contribute to a more sustainable future. This approach not only meets regulatory demands but also positions companies better within a competitive market increasingly focused on sustainability.

2.2. Machine Learning and Data-driven Optimization in the Development of more Sustainable Mechatronic Systems

While the literature on mechatronic systems such as laser machines has often placed a secondary emphasis on sustainability, this aspect is increasingly becoming a focal point in broader manufacturing research [9]. A contribution to this field is the systematic literature review by Sihag and Sangwan (2020) [10], which focuses on the energy consumption of machine tools. This review categorizes and models energy consumption, explores strategies for reducing energy use, and evaluates approaches to enhancing energy efficiency. By analyzing over 226 articles, Sihag and Sangwan (2020) [10] provide a comprehensive overview of the research conducted, highlighting both the achievements and the existing gaps in this area. Notably, their review underscores the critical but under-represented role of machine learning and data analytics in developing energy-saving strategies and assessing energy efficiency. It also emphasizes the need for deploying machining energy models to enhance the sustainability of machine tools. This literature review will serve as a pivotal guide for this paper, particularly concerning the classification and modeling of energy consumption.

Despite the increasing focus on sustainability within the broader manufacturing sector, literature specifically addressing the resource consumption of laser-cutting machine tools remains relatively scarce. This gap presents an opportunity for this research to contribute by applying established energy-efficient strategies to laser-cutting technologies.

The work of Kellens et al. (2014) [11] provides a crucial reference in this area, offering an environmental assessment of laser-cutting processes. This study not only identifies energy consumption as a major sustainability key performance indicator (KPI) but also highlights the roles of assist gas and waste material in the environmental impact of these processes. Moreover, Kellens [11] discusses strategies for improving resource and energy efficiency, which are vital for enhancing the sustainability of laser-cutting operations.

Further contributing to this discourse, Goffin et al. (2023) [12] conducted a case study that partially aligns with the aims of this research. Their research identifies several optimization strategies for laser-cutting processes, such as minimizing idle times and the number of idles, optimizing the arrangement of parts on sheets of metal, reducing machine power during idle periods, and refining processing parameters. These findings underscore potential areas for improving efficiency and reducing resource waste in laser-cutting applications.

Additionally, He et al. (2022) [13] reviewed various laser-cutting methods, including vaporization, fusion, and reactive melting cutting, detailing their benefits, applications, and environmental impacts. This review highlights significant environmental concerns associated with laser cutting, such as emissions of dust, smoke, and aerosols, which pose health risks. He et al. [13] propose several pollution control strategies, including advanced dedusting technologies like screen filtration, bag filtration, electrostatic filtration, and activated carbon filtration.

Collectively, these studies underline the need for targeted research on the environmental impact and optimization of laser-cutting machine tools, therefore this research offers valuable insights that could aid in bridging existing gaps and furthering sustainability in this field. The research focused on enhancing the environmental performance of laser-cutting machine tools has predominantly centered on CO2 lasers, with solid-state lasers receiving considerably less attention in the context of sustainability. This oversight highlights a significant gap in the literature, indicating an opportunity for pioneering research in this area.

3. Research Question and Methodology

The broader aim of this research is to support developers to utilize data analyses of field-gathered machine usage data, to optimize machine design for a more sustainable machine operation. Such optimizations are intended to enhance sustainability in the operation of mechatronic systems. This study specifically analyzes the resource consumption of laser-cutting machine tools, focusing on how different operational settings and programs influence energy and process gas usage. A data-driven approach using explainable machine learning techniques is used to gain deeper understanding of the prediction of resource consumption during machine operation. To operationalize the aim of this work, the following research questions are formulated:

- Q1: How can the resource consumption of laser-cutting machine tools be predicted and how well does such a prediction model perform?
- Q2: Which variables influencing the resource consumption of laser-cutting machine tools can be identified?
- Q3: In what ways can the gained understanding of resource consumption in laser-cutting machine tools inform strategies for achieving more sustainable production?

The methodological approach of this research is based on the Design Research Methodology (DRM) framework proposed by Blessing & Chakrabarti (2009) [14]. This framework outlines four distinct stages: Research Clarification, Descriptive Study I, Prescriptive Study, and Descriptive Study II, each designed to support a systematic investigation into optimizing laser-cutting machine tools through data-driven decision-making and the application of AI and machine learning techniques.

Stage 1, Research Clarification, involves conducting a literature review to define the research problem and uncover gaps in the current understanding of AI and ML applications for machine tool optimization. This stage develops focused research questions based on identified gaps, setting the foundation for the subsequent studies.

Stage 2, Descriptive Study I, includes detailed data collection, cleaning, and pre-processing. This stage aims to prepare a comprehensive dataset that accurately represents the operational parameters of laser-cutting machines. The meticulous preparation of data ensures its suitability for sophisticated analytical models, crucial for effective modeling and subsequent analysis.

Stage 3, Prescriptive Study, involves developing and optimizing predictive models using various machine-learning random forest regressions. These models are evaluated based on performance metrics as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Before, features get pre-selected over a stepwise linear regression based on the AIC.

Stage 4, Descriptive Study II, then focuses on analysing the significant features identified in the previous stage. This final phase leverages insights from feature impact analysis to propose data-driven improvements, aiming to enhance the efficiency and sustainability of laser-cutting operations. The culmination of these stages synthesizes the findings into actionable insights for advancing sustainable manufacturing practices.

4. Data Overview

The dataset aggregates data from various sources, primarily from the internal analytics data of a German machine tool manufacturer on a fully automated solid-state laser-cutting machine tool, and encompasses specific resource consumption data alongside technical and logistical parameters. Initial data collection involved sensors on the machine to record the consumption of electric energy and process gases (compressed air, nitrogen, oxygen) over a time span of three months. The detailed consumption data is recorded on a per-second basis, with subsequent conversions to align data granularity with program runs, crucial for linking broad data spectrums to proposed consumption metrics.

The data from pre-production programming and operations significantly enrich the dataset. This standardized JSON data varies per machine functionality, providing critical operational contexts such as laser settings and metal sheet specifications. The programming data includes detailed variables like laser power, speed, gas pressure, and cutting kerf under various scenarios. Additionally, geometry data extracted from program runs include metrics on part contours, areas, and complexity metrics like undercuts, which are vital for assessing the operational efficiency and resource consumption of the machine tool.

Further, data generated directly by the machine during production offers refined or modified operational data, enhancing the dataset with insights into machine performance and operation. This category includes characteristics of parts produced and details on program runs, such as operational states, durations, and machine feed rates. This layer enriches the analysis by providing a nuanced view of the machine's operational dynamics and efficiency, essential for the research's focus on environmental performance and optimization.

Pre-processing included data cleaning, handling of missing values, and management of outliers and interruptions. Missing values were addressed by assigning zeroes or excluding incomplete data entries, ensuring dataset integrity. Outlier management retained significant outliers to capture a comprehensive view of operational variability. The distribution analysis involved transformations to correct skewness in the data, enhancing the interpretability and reliability of the analysis. The final dataset consisted of 898 program runs, data points, 51 features, and four target variables for resource consumption with *electrical energy, nitrogen, oxygen, and compressed air.*

5. Prediction of the Resource Consumption of Mechatronic Systems

The first research question of this work critically examines the predictability of resource consumption for laser-cutting machine tools, focusing on the robustness and accuracy of developed predictive models. The methodology involved a rigorous selection and pre-processing of variables that significantly explain observed variances in the dataset. This process is crucial for identifying and training the most suitable predictive models for four key consumption metrics: energy, compressed air, nitrogen, and oxygen. Each model's performance was quantitatively assessed using three statistical metrics: mean-squared-error (MSE), root-mean-squared-error (RMSE), and symmetric mean absolute percentage error (SMAPE).

Energy Consumption Analysis: The analysis starts with a correlation study to determine which features significantly influenced energy usage. Only six variables displayed absolute correlations greater than 0.5, which quantifies the strength and direction of the relationship between two variables, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no correlation. A comprehensive model using stepwise linear regression guided by the Akaike Information Criterion (AIC) initially included 15 variables, of which 9 were significant to the 0.05 level, but an iterative refinement process was applied due to multicollinearity concerns, ultimately focusing on 8 variables. Performance metrics for this refined model were reliable, achieving an MSE of 0.214, RMSE of 0.465, and SMAPE of 4.45%, indicating high accuracy in predicting energy consumption.

Compressed Air Consumption Analysis: Despite initially weak correlations among the dataset features with compressed air consumption, the stepwise regression model includes seven variables that explain approximately 97% of the data variance (R^2 of 0.974). This model identified five significant variables, with two variables dropped due to multicollinearity and minimal impact on the model's predictive capacity. The complex dynamics of compressed air usage in laser-cutting operations seem not to be captured thoroughly, with an MSE of 1.346, RMSE of 1.216, and SMAPE of 48.96%.

Nitrogen Consumption Analysis: The nitrogen model is developed under the challenge of low initial correlations. Through stepwise regression, 12 variables were initially selected, however, due to multicollinearity and overlapping predictive influence, one variable was dropped. The remaining 11 variables significantly contributed to achieving an R^2 of 0.935. The performance metrics revealed an MSE of 4.76, RMSE of 2.33, and SMAPE of 24.2%, indicating sufficient predictive accuracy across varied operational conditions despite the complexity of variable interactions.

Oxygen Consumption Analysis: The oxygen consumption model showed the strongest initial correlations, with seven variables demonstrating significant relationships. After stepwise regression and further evaluation for multicollinearity, one variable was excluded, leaving six impactful variables. This model achieved an exceptionally high R^2 of 0.996, illustrating its nearly perfect explanatory power. The robust model demonstrated its precision with an MSE of 0.072, RMSE of 0.268, and an SMAPE of 2.2%, making it the most accurate of the consumption models developed. These analyses underscore the complexity and challenges of predictive modelling in industrial applications. The systematic approach of variable selection, assessment for multicollinearity, and iterative refinement of models ensured the development of reliable predictive tools. These models provide crucial insights into the operational efficiency and resource management of laser-cutting machines, offering significant opportunities for optimization and advancing sustainable manufacturing practices.

6. Influencing Parameters of the Resource Consumption of Mechatronic Systems

The sufficient to very accurate performances of the prediction models lead to a further analysis of feature importance, particularly focusing on models that show stronger performance. To quantify the impact of each feature on the model outcomes, the SHAP (SHapley Additive exPlanations) method is used [15]. This game-theoretic approach assigns Shapley values to distribute the predictive contributions equitably among the features, providing a clear and interpretable measure of each feature's influence. In the energy consumption model, eight variables stood out from an original set of 51 for their significant impact on predictions. The SHAP analysis consisted of different plots showing the influence of features on the models and revealed that the total duration of operation was the most dominant feature, far outweighing the influence of the other seven variables. This finding underlines the critical role of operational time in determining energy consumption, suggesting potential areas for efficiency improvements within laser-cutting operations. The SHAP values for a specific prediction instance indicate how each feature adjusted the base prediction value. Notably, the total duration of running alone adjusted the base value by about 8%, highlighting its substantial impact compared to other features. This analysis provided deep insights into the complex interplay of features and underscored the significant role of operational time in driving energy consumption. The bee swarm plot (see figure 1) further emphasized the importance of operational time, showing a linear relationship between running time and its effect on the model's predictions. It shows how the single predictions, seen as the points, affect the model output. While the colour indicates the size of the input values, showing small values in blue to high values in red, the SHAP values show a positive or negative impact on the model output. This plot confirmed that while other features contributed to the accuracy of the model, their impact was minimal compared to the duration of operation. This insight is crucial for understanding the driving factors of energy consumption and for identifying strategies to enhance energy efficiency.

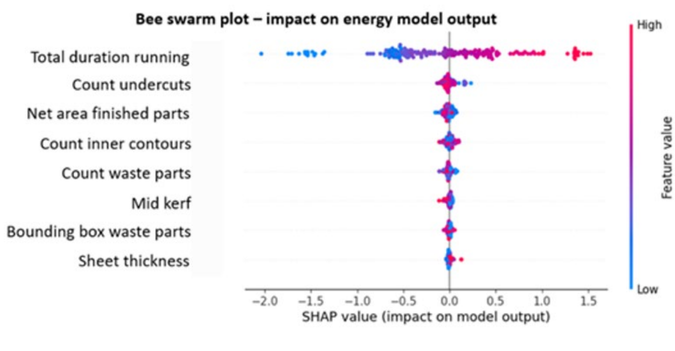

Fig. 1. Bee swarm plot for the energy model.

For compressed air consumption, the SHAP analysis also identified the total duration of running as the most impactful variable, with its influence even more pronounced than in the energy model. Additional variables like the count of inner contours and mid-normal gas pressure also significantly affected compressed air consumption, highlighting a complex set of interactions influencing this resource use. The corresponding waterfall plot (see figure 2) for compressed air demonstrated how each feature influenced a specific prediction, with operational time again playing a dominant role. This detailed breakdown helped to unravel the interactions among features that determine compressed air consumption for a specific program run. The bee swarm plot for compressed air revealed a pronounced impact from variables beyond operational time, providing insights into how different feature values contribute to the model's output. This plot highlighted the influence of material properties, represented by the e-module, and operational parameters like gas pressure and speed, on compressed air consumption.

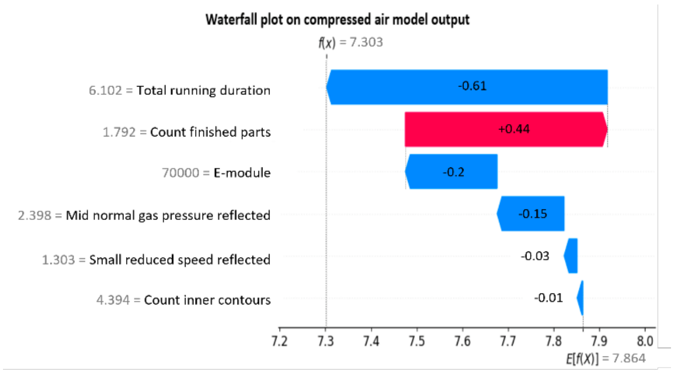

Fig. 2. Waterfall plot for the compressed air model.

Lastly, the analysis of nitrogen and oxygen consumption models reiterated the significant influence of operational time. In both cases, the total duration of running emerged as the most critical predictor, dominating the model outcomes, and affirming its universal role across different types of resource consumption in laser-cutting processes. For the oxygen model this is illustrated by the average absolute SHAP values of each feature in figure 3.

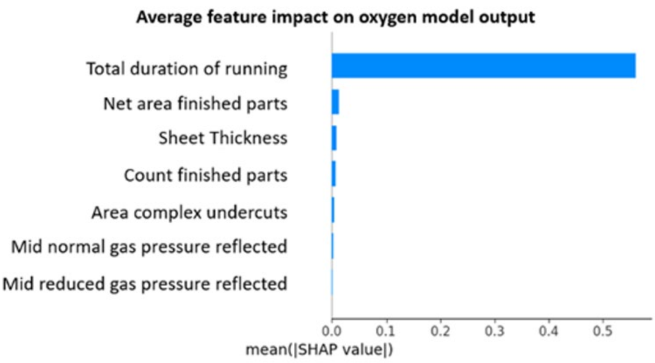

Fig. 3. Average SHAP values for the oxygen model.

These findings not only illustrate the efficacy of predictive models in understanding resource consumption but also emphasize the importance of operational time as a key factor across all models. This comprehensive analysis using SHAP provided valuable insights into the behavior of predictive models and highlighted critical features that significantly determine resource consumption in laser-cutting operations.

7. Enhancing the environmental performance in the operational phase

Building on confirmation that running duration significantly affects resource consumption in laser-cutting processes, a detailed analysis is conducted, to understand the underlying factors influencing operational times. This deeper scrutiny utilized a similar analytical framework that proved effective in previous models. The analysis starts with a correlation analysis which suggests that, although most features showed low correlation, seven features exhibited correlations exceeding 0.5, indicating their potential importance in predicting operational times. This pattern, consistent with earlier model behaviors, suggested a basis for robust model performance. To refine the selection of influential variables, stepwise linear regression is applied, initially identifying 31 variables that improve the model's predictive accuracy as evidenced by changes in the AIC. Of these, 23 variables are statistically significant. To enhance the model's robustness, 18 features are subsequently dropped due to multicollinearity or minimal impact, focusing the analysis on the most significant factors affecting running durations. The refined set of variables includes operational, technical, and design elements such as total contours, count of finished parts, and big kerf. These variables were crucial in determining the length of program runs in laser-cutting operations. A random forest model is subsequently trained to predict running durations, which demonstrate excellent accuracy. The model's effectiveness is confirmed by metrics such as an MSE of 0.029, a RMSE of 0.167, and a SMAPE of 1.31%, indicating precise predictions across most data points, aside from two slightly underpredicted and anomalously long durations. To understand the intricacies of the model's predictions, the SHAP analysis is applied. This analysis highlights the total length of contours as the most influential feature on running duration, underscoring its critical role in operational efficiency. Unlike its dominant impact in resource consumption models, the total contours length has a significant but less pronounced influence here.

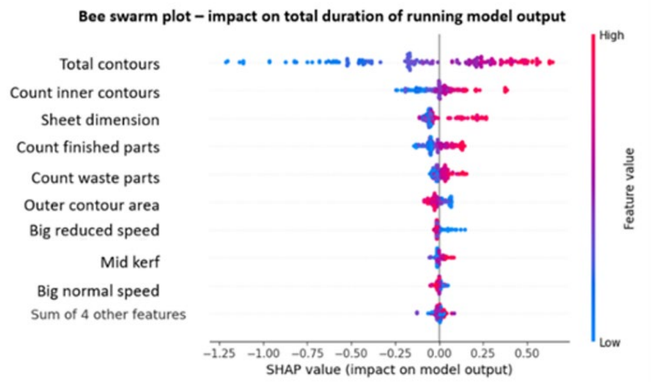

Fig. 4. Bee swarm plot for the running duration model.

Further analysis using SHAP values and feature contributions elaborated on the roles of various features. The analysis showed that total contour length had a substantial impact on model predictions, with the number of inner contours also emerging as notably influential, albeit to a lesser extent. Other features have minimal impact.

The bee swarm plot (see figure 4) reinforced the linear association between feature values and SHAP values, particularly highlighting how the total number of contours predominantly influenced the model's output. This plot also shows the impact of sheet dimensions, and the number of finished or waste parts, providing a comprehensive view of the factors driving running durations in laser-cutting operations.

8. Discussion and Outlook

The study on energy and gas consumption in laser-cutting processes employing XML techniques identified total operation duration as a pivotal factor affecting resource use across different models such as energy, compressed air, nitrogen, and oxygen. Findings highlight that consumption patterns are strongly linked to operational time rather than machine-specific settings, due to the automated nature of the laser machines studied and the high constant consumption of the machine. This insight emphasizes the impact of machine design over manual adjustments, suggesting that reducing operational times could significantly enhance efficiency and sustainability in laser-cutting environments.

Discussion within the research points towards the negligible effect of machine settings on resource consumption, underlining the importance of operational efficiency for sustainability. The exclusion of runs with interruptions, which generally show higher consumption, further validates the need for continuous operations without stops. These conclusions focus on optimizing machine run durations, which can be directly addressed by part design and complexity, and maintaining uninterrupted operations as key strategies for reducing energy and gas use, thus promoting a more sustainable production approach. This study presents promising results; however, further validation is necessary to enhance the generalizability of these findings. The analysis was conducted using data from a single machine type with a very high degree of automation, which may limit the applicability of the results to other systems. To robustly compare the outcomes, additional data from a variety of machines across different operational environments are required. This expansion of the dataset would allow for a more comprehensive assessment of the model's performance and its potential variability. Thus, future research should focus on incorporating a broader array of data sources to substantiate and extend the conclusions drawn in this study.

Future research should explore methods to optimize production speeds and minimize idle times, aiming to reduce costs and environmental impact. This research suggests incorporating design elements as contour length and inner contour counts as environmental KPIs of sheet-metal parts to be cut, potentially leading to significant reductions in resource consumption and fostering more sustainable practices in the manufacturing sector.

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