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From Production Data to Resource Efficiency: A Case Study on Machining Operations

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Abstract. As the manufacturing industry moves towards responsible consumption and production, manufacturers are intensifying their focus on enhancing resource efficiency. While resource efficiency in manufacturing is understood conceptually, measuring and managing it is challenging in practice. Though many factories are data-rich, it is often difficult to use data effectively in assessing resource efficiency. With the aim of demonstrating production data's key role in resource efficiency, this study presents an approach for evaluating resource efficiency using readily available production data through a use case of lubricant usage on machining operations. The machining equipment were grouped into four categories based on their lubricant consumption and running time in the results. Results also found significant variations across identical machines. The identification of hotspots and role models, as well as the quantified lubricant efficiency gaps, can be translated into improvement actions, which positively impact sustainability practices in the company's daily operations. Future work will focus on diving deeper into the analysis of individual machines and extending the approach to other resource flows. This research supports an effective application of research-based methods for resource efficiency assessment in industry, encouraging the usage of available production data for more resource-efficient manufacturing.

1. Introduction

Resource efficiency refers to the ratio of product output to total resource input which is a core principle of achieving sustainable manufacturing (1). In manufacturing, resource efficiency can be translated in the form of efficient use of material, energy, water, and other inputs while minimizing environmental impact and operational costs (2). Resource efficiency is becoming a core strategy for manufacturing companies to stay competitive, because effective resource use has become critical advantage due to the rising resource scarcity and prices worldwide (3). Manufacturing companies are also being pushed to enhance their environmental sustainability performance through more efficient operation by regulations (4).

However, many manufacturing factories found it challenging to measure resource efficiency. Conventional approaches to resource efficiency or indicators often focus on isolated systems, missing opportunities for comprehensive analysis (5,6). Moreover, while manufacturing factories already collected a significant amount of data for production management and quality control

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purposes, this same data often remains underutilized for systematic assessment of resource efficiency (7). The challenge lies not only in data availability but also in developing systematic methodologies to transform raw operational data into actionable efficiency knowledge.

Together with this challenge, the manufacturing industry is also undergoing digitalization, which promises to transform traditional manufacturing facilities into smart manufacturing facilities focused on using real-time data to support accurate and timely decision-making (8,9). Production log, equipment performance metrics, energy consumption records, material usage tracking, quality measurements, maintenance logs, and environmental monitoring data are all examples of production data. In the era of digitalization, the explosion of data influenced a lot how production data is collected and analysed (10). Benefiting from digitalization, production data is also supposed to be used in supporting sustainable manufacturing from many different perspectives, including guiding sustainability assessments for data-informed and fact-based business decisions (11).

The gap between available production data and its effective utilization for resource efficiency assessment represents both a challenge and an opportunity for the manufacturing sector. To bridge this gap, this study has the research question: How can existing production data be systematically used to identify efficiency gaps and improvement opportunities?

2. Research approach

To investigate how manufacturing companies use production data to achieve resource efficiency, this study used a case study methodology. According to Yin's theory, case study research is particularly appropriate for real-world contexts (12). Focusing on real manufacturing settings, this case study investigates the practical challenges and generates findings that are both theoretically grounded and practically relevant for practitioners seeking to improve resource efficiency through better data utilization. Accordingly, the work followed the steps of case selection, data collection, data preprocessing, data analysis, and interpretation of results (shown in the Figure 1 below).

The case selection focused on the machining operation, which is one of the most important and resource-intensive production areas in the case study company. The company is a large-scale manufacturer, and this machining area includes multiple production lines and more than 30

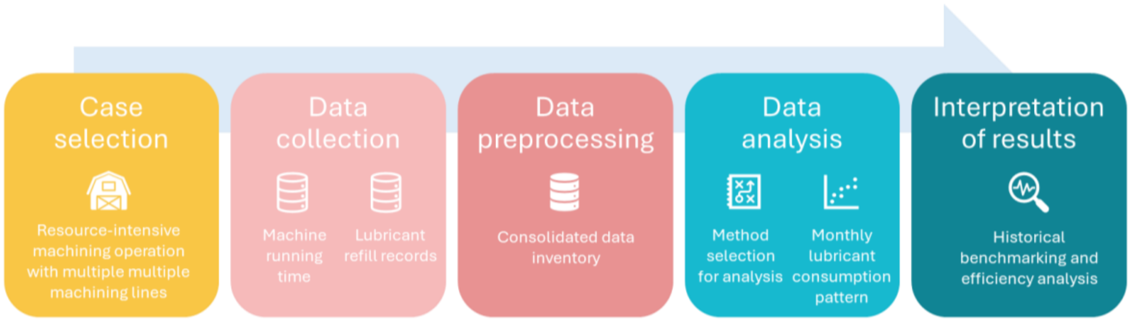

Figure 1. Steps of the research approach from case selection to interpretation.

pieces of machining equipment. Lubricant consumption in machining operation was selected as the focused resource flow, considering several critical sustainability viewpoints, such as the direct and indirect costs of consumption, the environmental impact of lubricant contamination, and the impact on operators' working environment. The selected area had lubricant consumption related data that make data collection and analysis feasible. Furthermore, the size of selected machining area and the type of machining processes can also provide good generalizability (as SMEs can have similar setting).

The next step, data collection, included machine running time (in hours) and lubricant refill volume (in Liters), recorded at both daily and monthly resolutions from the machining area. Several Gemba walks were arranged with people from different functions in the machining area to ensure good and accurate understanding of collected data (7). Details of collected data are presented in Table.1. The data set included Line ID, Machine ID, Running/Stop time, Lubricant refill time and quantity, etc.

The data of machine running and lubricant refills needed to be pre-processed before it could be used in subsequent analysis. In this study, collected raw data were consolidated to be used in the monthly lubricant efficiency assessment, as shown in the third box of Figure 1.

Table 1. Primary data collected from the machining area.

Data string	Planned running time	Machine stop time	Lubricant refill
Data resolution	For machining line	For machine	For machine
Data collecting frequency	Production plan	Record upon stops	Record upon refills
Data contents	Planned running time	Data contents	Planned running time
Data source	Production plan	Production log	Maintenance log
Data-collecting approach	Semi-automated	Semi-automated	Manually

Aligning the resolutions for system levels and period was the main task in the data preprocessing. The machine running time was calculated from the planned running time and the machine stop record. The quantity of refills and the interval between refills were used to calculate each machine's daily lubricant consumption. Data outliers such as a large volume of refill in a short period of time were identified and verified together with production engineers. Some of these outliners due to maintenance activities were taken out to assure the average values can properly reflect the machine’s typical state. Table 2 shows the consolidated data inventory.

Table 2. Data from the machining area ready for assessment after preprocessing.

Data string	Machine running time	Lubricant refill
Data resolution	Single machine	Single machine
	Monthly	Daily
Data contents	Running time Machine ID	Amount of refill Machine ID

After data preprocessing, monthly machine running time and daily lubricant consumption were stored in a table shown in Figure 2.

Machine ID	Month 1		Month 2		...	Month X	
	Running time	Lubricant consumption	Running time	Lubricant consumption	...	Running time	Lubricant consumption
					...		
					...		
					...		
					...		
					...		

Figure 2. Appearance of the consolidated data inventory.

For the data analysis and its method selection, this study used the opportunistic approach and the method library developed in an integration model for resource efficiency (13), where user choose feasible resource efficiency assessment methods from the method library in an opportunistic manner based on what production data they have. Data analysis method used in this paper was inspired by the method in a study to improve the energy and resource efficiency of manufacturing companies (14). To create graphical representations of consumption patterns, this study first plotted lubricant consumption against machine operational data using pre-processed data. The consumption patterns were used to establish zones that are efficiency or inefficient and machines with similar efficiency were grouped in different zones.

Based on the data analysis, machine's lubricant efficiency was interpreted through different data analytics techniques, such as benchmarking, hotspot analysis, and performance correlation. The interpretation of analysis results also supported the quantification of improvement potential on top of benchmarking lubricant efficiencies between machines.

3. Results

A visualization of lubricant efficiency is presented. Data in the results and discussion study were anonymised from actual production data and information.

3.1 Results of data analysis

A table that can automatically read data in the consolidate data inventory for a chosen month and line was developed for the visualisation (shown in Figure 3). This table also contains the average, medium, and ¼ quart values for lubricant consumption and machine running time.

Month	1	
Machine ID	**Running time (hour)**	**Lubricant consumption (liter)**
1	125,32	0,12
2	93,96	0,04
3	100,35	0,08
4	128,44	0,08
5	150,66	0,88
6	83,94	2,02
7	133,98	0,95
8	90,86	0,04
9	91,69	0,04
10	121,68	0,32
11	122,32	3,29
12	116,56	0,20
13	93,75	0,16
14	122,67	0,52
15	108,23	0,49
Average/Mean	112,29	0,61
Median	116,56	0,20
1/4 quart	93,75	0,88

Figure 3. Appearance of the table that reads data from the consolidate data inventory for selected month and machines.

As illustrated in Figure 4, the machine-level lubricant efficiency was plotted using running time and lubricant consumption as key indicators. The boundaries for the efficiency categories are defined based on the median values of these two parameters across the dataset.

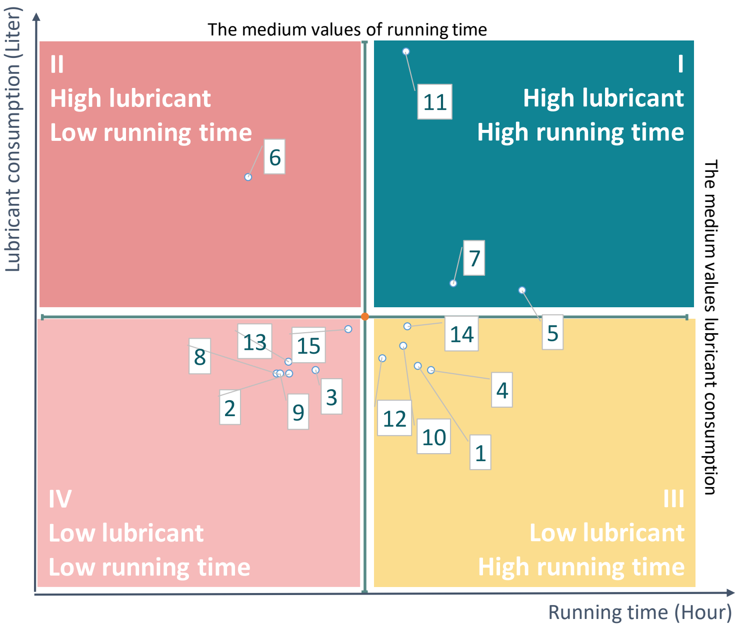

Figure 4. Machine grouped by lubricant efficiency.

The four segments in Figure 4 illustrate four equipment groups based on their lubrication efficiency: Category I stands for high lubricant use and long running time; category II for high lubricant use and short running time; category III for low lubricant use and long running time; and category IV for low lubricant use and short running time. Operations with running time above the median and lubricant consumption below the median are therefore classified as more efficient. This approach enables an internally consistent comparison of performance across different machining operations.

However, this median value-based plot distinguishes better and worse performance within the existing operations comparatively, but do not imply that machines classified as more efficient represent optimal or achievable efficiency. The boundary values can therefore be adjusted based on expert knowledge of the machining processes and established benchmarks. Such adjustments would allow the categorisation to move beyond relative performance towards a more normative definition of efficiency, aligned with theoretically ideal operations or industry best practice.

3.2 Interpretation of lubricant efficiency

The machining operation's lubricant efficiency was interpreted from two aspects: lubricant efficiency overview, and improvement target setting. In this study, "benchmarking" refers specifically to historical benchmarking, where each machine's lubricant efficiency is compared to its own past performance and to other identical machines over time.

This visualisation initially shows the efficiency ranking of machines as an overview. Machines with high lubricant use and regardless of the running time, such as machine 6 and 11, were identified from the four machine categories. These devices were found to be hotspots that controlled the machining operation's lubricant consumption. On the other hand, "role models" were machines that used less lubrication but had longer operating times. For example, the machine 10 had a good lubricant efficiency because its low lubricant usage while it still ran relatively high number of hours in the first month.

Lubricant efficiency was compared throughout months for the same machine and identical machines in the same machining station by categorizing machining equipment according to the same criteria over time. In this case study, machining equipment with similar operating conditions was also benchmarked. For instance, machines 6 and 8 are two identical machines in the same machining station. Their running times in the first month were similar but machine 6 had much higher lubricant consumption than machine 8. This pair of machines will be continuously monitored by maintenance team.

The top-performing machining equipment was viewed as efficiency targets in the monthly lubricant efficiency overview and benchmarking across months and lines. To establish improvement goals, the gaps between hotspot equipment and top-performing machining equipment were examined. But prioritizing the improvement potentials also requires consideration of machine characteristics, such as the number of years in operation and the lubricant supply systems. As visualized in Figure 4, machine 4 had very good lubricant efficiency however its performance was not the best for target setting since it is the youngest machine with advanced controlling system in the machining area.

4. Discussion

4.1 Contribution of the study

This study contributes to both industrial practice and academic research by demonstrating a systematic approach to transforming production data into actionable insights for resource efficiency improvement in manufacturing environments. By linking machine operational states with resource consumption data, the study shows how existing production data can be utilised to identify patterns, variations, and improvement potential in machining operations. The proposed approach enables companies to establish an internal baseline for benchmarking and to develop insights into specific, quantifiable differences in performance. These insights are crucial for prioritising improvement areas and for supporting decision-making in resource efficiency initiatives.

From an industrial perspective, the study demonstrates how companies can move beyond aggregated indicators towards a more granular understanding of resource consumption at the machine level. By identifying variations between machines, the approach supports the identification of inefficiencies that are difficult to detect in complex production systems. A key contribution of this study is the attempt to define resource efficiency using running time and lubricant consumption as indicators, combined with a classification based on median values. This relative definition of efficiency enables internal comparison across operations and supports the identification of comparatively better and worse performance within the existing production context. While this approach does not claim to represent theoretically optimal or best-practice efficiency, it provides a pragmatic and transparent starting point for analysing resource use in real industrial settings where detailed process models and ideal benchmarks are often unavailable.

From a research perspective, this study addresses the gap between theoretical resource efficiency methods and their practical application in industrial contexts. Although numerous assessment methods and indicators have been proposed in the literature, their implementation in real manufacturing environments is often constrained. Through an in-depth case study, this research contributes to the validation of resource efficiency methods under real-world conditions. This study provides empirical evidence on how resource efficiency concepts can be demonstrated by using industrial data, thereby supporting future research aiming to bridge sustainability theory and manufacturing practice. Furthermore, this study also pointed out the potential to refine boundary values through expert knowledge and benchmarks. This opens a pathway for future work to integrate theoretical models, best-practices, and expert judgement.

4.2 From production data to information and knowledge for resource efficiency

While prior studies have focused on predefined indicators by employing approaches such as life cycle assessment (LCA) to compare lubrication strategies to quantify relative process efficiency (15,16), they typically assume that production data are clean and well-structured. Studies that applied simulation (17) or mathematical modelling (18) for efficiency improvement can even require good data input. The challenges associated with raw industrial data such as inconsistent machine state, misaligned timestamps, and missing values are rarely addressed in detail. Built upon prior studies, this study addresses the data preprocessing challenges in industrial machining data. It also provides insight in how efficiency can be defined and classified and offers a flexibility that efficiency can be refined through expert knowledge and benchmarks.

As this study aimed, a consistent data inventory for lubricant efficiency evaluation was developed. The inventory with formatted tables is easier to use compared to working directly with primary data. The transforming from data to knowledge can be cascaded through three levels: data, information, and knowledge (19). This case study demonstrates a successful transition from data to information level. By systematically identifying available data, prioritizing critical resource flows, consolidating raw data into structured data inventories, and applying appropriate analytical methods through a guided method selection, manufacturing companies can extract information from these visualizations to understand their resource efficiency. However, data and information are not sufficient for improvement (20). In this paper, the visualization only serves as a starting point, showing performance differences and efficiency gaps across equipment and operations. Transforming this information into actionable knowledge, which means specific improvement measures can be identified and implemented (21), currently relies largely on input from experts such as machine operators and process engineers. Expertise from production line needs to be integrated systematically, such as regular workshop to interpret the observed efficiency patterns, understand their underlying causes, and formulate appropriate actions. The implementation of improvement actions also requires deeper involvement from operational personnel. Long-term follow-up studies are therefore important to validate the generated knowledge.

4.3 Future work

Using the production data that was available, the case study conducted a groundwork for a practical evaluation of resource efficiency.

The relative, median value-based efficiency boundaries used in this study will be refined by integrating expert knowledge and process-specific benchmarks. This will enable the transition from purely data classification towards a more normative definition of efficiency, aligned with what is considered theoretically ideal and practically achievable in machining operations.

Future work will also focus on identifying specific variables that influence lubricant efficiency at the individual machine level. The operational parameters, maintenance plans, process circumstances, and equipment feature that affect consumption variances will be investigated. Future studies should seek to understand the underlying causes of efficiency gaps by analysing these variables. Moreover, timely monitoring can be realized to support better root cause analysis. Engineers will be able to corelate consumption trends to certain operational events, maintenance tasks, and process modifications with the help from real-time data collection. The identification of immediate causes of efficiency losses is important to enable rapid response in production. To build predictive models for lubricant consumption with artificial intelligence and machine learning technology can potentially make lubricant efficiency management more proactive (22), though advanced modelling could put higher requirement on production data.

In terms of scale-up, the data inventory table can be used in future research to investigate other time scales. Regardless of the frequency or granularity of data gathering, flexible time scales will optimize its usefulness. Higher resolution, such hourly or daily, can help with detection of recent efficiency fluctuations and timely correction actions. Trends at a lower resolution can also strategically support longer-term study, like in quarterly or annual planning. Building upon the current lubricant-focused analysis, future work will scale up to efficiency assessment of different resource flows, such as energy use.

5. Conclusions

This study addressed the opportunity to utilize available production data for resource efficiency assessment in manufacturing. While generating a huge amount of data from operation, most manufacturers did not use the data systematically for resource efficiency improvements.

This case study provides a practical approach that manufacturing companies can implement using existing production data to generate insights about lubricant efficiency. The structured data inventory tables simplify future work compared to working with raw data sources. The successful transformation from data into information also helps the case company identify performance variations and improvement opportunities. However, translating the information into concrete knowledge and actions still requires expert input from operators and engineers. This information-to-knowledge gap represents a practical challenge that extends beyond the analytical framework and was not fully explored within this study.

This study demonstrates that even simple, existing production data can drive meaningful improvements in resource efficiency, without costly new data infrastructure, but using only existing production data through a structured approach. By providing practical tools and instructions, this research makes resource efficiency assessment more accessible to manufacturing companies, supporting the transition toward resource-efficient manufacturing.

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