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ASSESSMENT OF DATA COLLECTION TECHNIQUES IN MANUFACTURING AND MECHANICAL ENGINEERING THROUGH MACHINE LEARNING MODELS

Md Aliahsan Bappy[1], Manam Ahmed[2]
[1]Mechanical Engineering, College of Engineering, Lamar University, Texas, USA
https://orcid.org/0009-0008-8585-1512
[2]Mechanical Engineering, College of Engineering, Lamar University, Texas, USA
https://orcid.org/0000-0003-0946-2183

Abstract

This research conducts a systematic literature review and case study analysis to compare the Design of Experiments (DOE) and Active Learning (AL) methods in the context of machine learning within manufacturing and mechanical engineering. The objective is to evaluate the efficacy of these data-gathering methods in informing Supervised Machine Learning models. The review began with a search yielding 1280 documents, culminating in a final selection of 35 articles after meticulous screening and eligibility checks. The findings illustrate that DOE methods provide comprehensive insights into process variables, while AL methods offer significant efficiency gains by requiring less data to achieve similar or improved model performance. Case studies demonstrate the practical applications and highlight the potential of a hybrid approach that integrates the thoroughness of DOE with the efficiency of AL. The research identifies gaps in the current literature, particularly in the real-world application of AL and its integration with emerging technologies. The conclusion suggests that future research should focus on developing sophisticated AL models to navigate the increasing complexity of manufacturing environments and that a nuanced approach to selecting data-gathering methods is crucial.

Keywords: *Machine Learning Models, Data Gathering Methods, Manufacturing Process Optimization, Mechanical Engineering, Active Learning Algorithms*

Introduction

Data gathering is increasingly critical in mechanical engineering and manufacturing, particularly in integrating Supervised Machine Learning (ML) models (Amini et al., 2023). These models demand precise and extensive datasets to effectively simulate and enhance complex mechanical systems (Cheng & Jin, 2021). Given the interconnected nature of variables in manufacturing, data quality profoundly affects the performance and reliability of ML models (Freiesleben et al., 2020), emphasising the need for effective data-gathering methodologies. While reliable, traditional data-gathering methods, such as the Design of Experiments (DOE), often struggle with scalability and efficiency in Supervised ML models, which require vast and varied datasets (Duan & Ries, 2007). Active Learning (AL), an emerging paradigm in ML, offers a promising solution by selectively targeting informative data points, potentially reducing the required data volume (Duan & Ries, 2007). However, the practical application and effectiveness of AL compared to conventional DOE methods in industrial settings remain under-researched (Gubernatis & Lookman, 2018). The integration of ML in manufacturing signifies a paradigm shift, enhancing data acquisition and analysis capabilities (Amar et al., 2019). This research aims to leverage ML's potential in refining data-gathering methods critical for developing and optimising manufacturing processes and material properties (Freiesleben et al., 2020). In additive manufacturing (AM), understanding the variables affecting material properties and outcomes is essential for achieving quality and performance (Gubernatis & Lookman, 2018). Critical studies, such as the one by (Korany et al., 2015), have explored the impact of microstructure on the mechanical properties of materials like Ti-6Al-4V, revealing the complex interplay between manufacturing conditions and material properties. Similarly, research by (Liu et al., 2020) focuses on process parameter optimisation in manufacturing stainless steel 316L parts, highlighting the heterogeneity of mechanical properties in AM (Green et al., 2019). The use of ML in predicting material properties, as shown in Arboretti et al. (2021) study, demonstrates the effect of manufacturing parameters on the mechanical properties of 3D-printed parts, showcasing ML's capability in advanced data analysis (Cheng & Jin, 2021). Comprehensive reviews by Salmaso et al. (2019) and Arboretti et al. (2021) provide insights into the microstructure and mechanical properties of metals in AM, emphasising the need for sophisticated data-gathering methods (Amar et al., 2019). This study aims to develop a sophisticated ML model to evaluate data-gathering methods in manufacturing and mechanical engineering, intending to create a model that accurately interprets data and identifies optimal data acquisition strategies. This research contributes to the evolution of manufacturing technologies, promoting efficiency, cost-effectiveness, and quality. Positioned at the intersection of ML, mechanical engineering, and materials science, this study charts a new course for the future of manufacturing technology. This literature review also aims to thoroughly compare traditional DOE and the novel AL methods in data gathering for Supervised ML models in manufacturing and mechanical engineering. It seeks to evaluate the effectiveness of these methods in generating high-quality datasets and their applicability and efficiency across various industrial scenarios. The significance of this study lies in its potential to guide future data-gathering approaches in mechanical engineering and manufacturing, especially in the context of Supervised ML models. The review's findings are anticipated to significantly contribute to academic and industrial practices, offering insights and practical guidelines for selecting optimal data-gathering methods. This could lead to more efficient, cost-effective, and higher-quality manufacturing processes.

Literature Review

Design of Experiments (DOE) Methods

Design of Experiments (DOE) is a crucial method in data collection, particularly revered for its systematic approach in mechanical engineering and manufacturing. Its structured framework facilitates the testing and evaluating of variable impacts and is a cornerstone in process optimisation and control (Jadhav et al., 2021). According to Kandar and Akil (2016), the application of DOE spans various aspects of manufacturing, from material selection to process optimisation, enabling engineers to understand the effects and interactions of multiple factors comprehensively. For instance, in the automotive industry, DOE is instrumental in optimising manufacturing processes to enhance vehicle performance and fuel efficiency (Beg et al., 2019). The robustness of DOE lies in its methodical approach, which allows for a thorough investigation of process parameters, thereby aiding in decision-making and quality improvement in manufacturing operations (Weinmann et al., 2003).

The strength of DOE methods primarily lies in their ability to efficiently unravel complex interactions among numerous factors (Shi et al., 2004). This feature is particularly beneficial in scenarios where multiple variables simultaneously influence the output or quality of a process (Nouby et al., 2009). A

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prime example is factorial design, a type of DOE which enables the analysis of the effects of several variables at different levels with a relatively low number of experiments (Jadhav et al., 2021). This efficient exploration of a wide range of process conditions significantly reduces time and resources, which is especially vital in large-scale manufacturing settings (Antony, 2023). Additionally, DOE methods contribute to developing more reliable and robust manufacturing processes by facilitating a deeper understanding of the process behaviour under various conditions. This, in turn, helps identify the optimal settings for maximum efficiency and quality (Korany et al., 2015).

Despite its widespread application and advantages, DOE methods are not without limitations. One of the primary challenges is the increasing complexity that arises in experiments involving many factors (Freiesleben et al., 2020). This complexity can lead to difficulties in experimental design and data interpretation, potentially affecting the accuracy of the outcomes (Alagumurthi et al., 2006). Additionally, the effectiveness of DOE heavily relies on the accuracy of the initial assumptions about the relationships between variables. Incorrect assumptions can lead to misleading results, which can have significant implications, especially in high-stakes manufacturing processes (Robinson et al., 2003). Furthermore, in the rapidly evolving landscape of manufacturing technology, where new materials and processes are continuously introduced, traditional DOE methods may struggle to keep pace with the need for rapid and adaptive experimentation strategies (Vining, 2011).

Active Learning (AL) Methods

Active Learning (AL) is revolutionising the approach to data gathering in mechanical engineering and manufacturing, particularly within the scope of Supervised Machine Learning (ML) (Zhang et al., 2020). This innovative method is characterised by its iterative learning process, where the ML model actively selects specific data points for querying, thereby enhancing its learning efficiency (Alemohammad & Shahini, 2010). Unlike traditional learning methods that passively use the entire dataset, AL strategically focuses on the most informative data. This targeted approach significantly minimises the data required for training, making it a game-changer in scenarios where data collection is resource-intensive or data is scarce (Alemohammad & Shahini, 2010; Wende et al., 2020). The application of AL extends beyond mere data reduction; it plays a critical role in refining model accuracy, particularly in complex manufacturing processes where precision is paramount. For example, in predictive maintenance of manufacturing equipment, AL can pinpoint the most critical data, leading to more accurate and timely predictions (Tembe & Kamble, 2016; Xu, 2017).

The versatility of AL has led to its increasing application in diverse areas of mechanical engineering. One significant area is material property prediction, where AL aids in identifying key material characteristics under varying manufacturing conditions (Bamberg et al., 2010). This is especially beneficial in the additive manufacturing sector, where understanding material properties like tensile strength and fatigue resistance is crucial for product quality. Another notable application is process optimisation, where AL enhances efficiency and reduces waste by identifying optimal process parameters (Christie & De Graaff, 2017). For instance, in the automotive industry, AL can be used to determine the best combination of factors for achieving optimal engine performance (Duan & Ries, 2007; Tian et al., 2020). These applications demonstrate AL's capability to handle complex, multi-variable scenarios typical in mechanical engineering, providing substantial benefits in terms of resource savings and improved process outcomes (Cheng & Jin, 2021; Zhu, 2022).

Despite its advantages, implementing AL in mechanical engineering and manufacturing is not without challenges (Ledezma-Ramírez, 2023). One primary challenge is identifying the most effective querying strategies that balance the trade-off between exploration (acquiring new knowledge) (Rouco et al., 2018) and exploitation (using known information) (Greenhill et al., 2020). This requires sophisticated algorithms to decide which data points yield the most valuable information (Politis et al., 2017). Another significant challenge lies in integrating AL into existing manufacturing systems. This integration demands a technical alignment with current processes and machinery and a cultural shift within the organisation towards data-driven decision-making (Greenhill et al., 2020). Manufacturers need to ensure that their infrastructure can support AL algorithms and that their personnel are trained to interpret and act on these systems' insights. Overcoming these challenges is essential for leveraging the full potential of AL in modern manufacturing environments.

Comparative Studies Between DOE and AL Methods.

The emerging body of comparative studies examining the Design of Experiments (DOE) and Active Learning (AL) methods is shedding light on their respective roles and efficiencies in data gathering for Machine Learning (ML) applications (Alagumurthi et al., 2006; Domagalski et al., 2015; Durivage, 2016; Granato & de Araújo Calado, 2014). These studies typically underscore the efficiency of AL in reducing the volume of required data without sacrificing the performance of ML models, a notable advancement over the traditionally exhaustive approaches employed by DOE (Jadhav et al., 2021). For example, research conducted by da Silva and Zanini (2004) contrasts the two methods in manufacturing process optimisation, revealing that AL can achieve comparable accuracy to DOE while utilising significantly fewer data points. This finding is pivotal as it suggests that AL can streamline data collection processes, thus saving time and resources. However, the studies also highlight that the effectiveness of AL hinges on the quality of the initial dataset and the specifics of the learning algorithm employed (Shin & Lee, 2011). This dependency indicates that while AL offers significant advantages, its implementation must be carefully tailored to the specific context and requirements of the ML application (Bayer et al., 2020; Freiesleben et al., 2020).

Despite the valuable insights provided by current research, noticeable gaps exist in the literature, particularly regarding applying AL in complex, real-world manufacturing scenarios (Alagumurthi et al., 2006). Most existing studies focus on controlled or simplified environments, leaving a void in understanding how AL performs under the multifaceted and often unpredictable conditions of actual manufacturing processes. Furthermore, there is a pressing need for more comprehensive comparative research that evaluates the performance of DOE and AL methods and their practicality and scalability in industrial applications (Cheng & Jin, 2021; Cho et al., 2021; Hernández-de-Menéndez et al., 2019). Such studies would help in assessing the real-world viability of AL, providing crucial data to guide its broader adoption in the manufacturing sector. Additionally, integrating AL with other emerging technologies, such as the Internet of Things (IoT) and digital twins, represents a significant untapped potential (Bamberg et al., 2010; Li et al., 2021; Zhu, 2022). Exploring how AL can synergise with these technologies could open new avenues for innovation in manufacturing, leading to more innovative, more efficient, and interconnected production systems (Christie & De Graaff, 2017). Addressing the identified gaps in AL research is critical for advancing the field and unlocking the full potential of this technology in manufacturing and mechanical engineering (Carvalho, 2006).

Methodology

In this research, a systematic literature review was executed following a stringent methodology anchored in the PRISMA guidelines, which dictate a transparent and methodical approach to synthesizing research findings. Our process commenced with an exhaustive search across Scopus and Web of Science, two databases renowned for their extensive repositories of scholarly articles, to harvest a preliminary set of documents pertinent to machine learning and data gathering methods in the domain of manufacturing and mechanical engineering. To ensure the integrity and relevance of our review, we applied Endnote, a sophisticated reference management software, to eliminate duplicate entries, thus refining our dataset to a more manageable and focused collection. This initial refinement was followed by a rigorous screening process, utilizing titles, abstracts, and keywords to filter out documents that did not directly align with our research objectives. Further scrutiny was conducted through a full-text assessment, adhering to predefined eligibility criteria to distill the selection to the most germane studies. The culmination of this process yielded a curated set of articles that specifically address the integration and evaluation of machine learning models and data gathering methods, illuminating their applications in optimizing manufacturing and mechanical engineering processes. By meticulously adhering to this methodological blueprint, our literature review stands as a comprehensive and academically rigorous examination of the existing body of work, laying a robust foundation for the insightful analysis and discussion that follows:

Identification

The initial search was conducted across two databases, Scopus and Web of Science, yielding 1280 documents.

Screening

After removing duplicates (120 duplicates were removed using Endnote), 1160 documents were retained. A further screening based on title, abstract, and keyword led to excluding 780 documents, leaving 380 documents.

Eligibility

Of the remaining 380 documents, 290 were excluded due to their focus on industries other than the one of interest for the review, and 35 were excluded due to the unavailability of full-text versions. This process resulted in 90 documents being eligible.

Final Selection

Out of the 90 eligible documents, a final set of 35 full-text documents was selected for review. These documents emphasised Machine Learning Models, Data Gathering Methods, Manufacturing Process Optimization, Mechanical Engineering, and Active Learning Algorithms and were included in the final review.

The methodology depicted in the uploaded flowchart outlines a systematic and rigorous process for selecting literature in a review, likely adhering to PRISMA guidelines. The initial identification stage commenced with a comprehensive search across two prominent databases, Scopus and Web of Science, resulting in a collection of 1280 documents. This was followed by a meticulous screening phase where duplicate entries were filtered out using Endnote, a reference management software, leaving 1160 documents for further evaluation. Subsequent screening involved a thorough review of titles, abstracts, and keywords, which led to the exclusion of 780 documents that did not meet the specific criteria, narrowing the field to 380 documents. The eligibility assessment stage focused on the relevance of the documents to the research domain, leading to the exclusion of 290 documents pertinent to industries outside the scope of the review. Additionally, 35 documents were discarded due to the lack of accessibility to their full-text versions, a crucial element for in-depth analysis. The culmination of this stringent process resulted in 90 documents deemed eligible for inclusion. In the final selection phase, 35 full-text documents were chosen based on their direct emphasis on the key topics underpinning the review: Machine Learning Models, Data Gathering Methods, Manufacturing Process Optimization, Mechanical Engineering, and Active Learning Algorithms. This final literature cohort represents a distilled essence of relevant research, ensuring a focused and comprehensive narrative for the systematic review. This process underscores the commitment to methodological rigour and relevance, ensuring that the review's findings are built upon a foundation of quality and pertinent literature.

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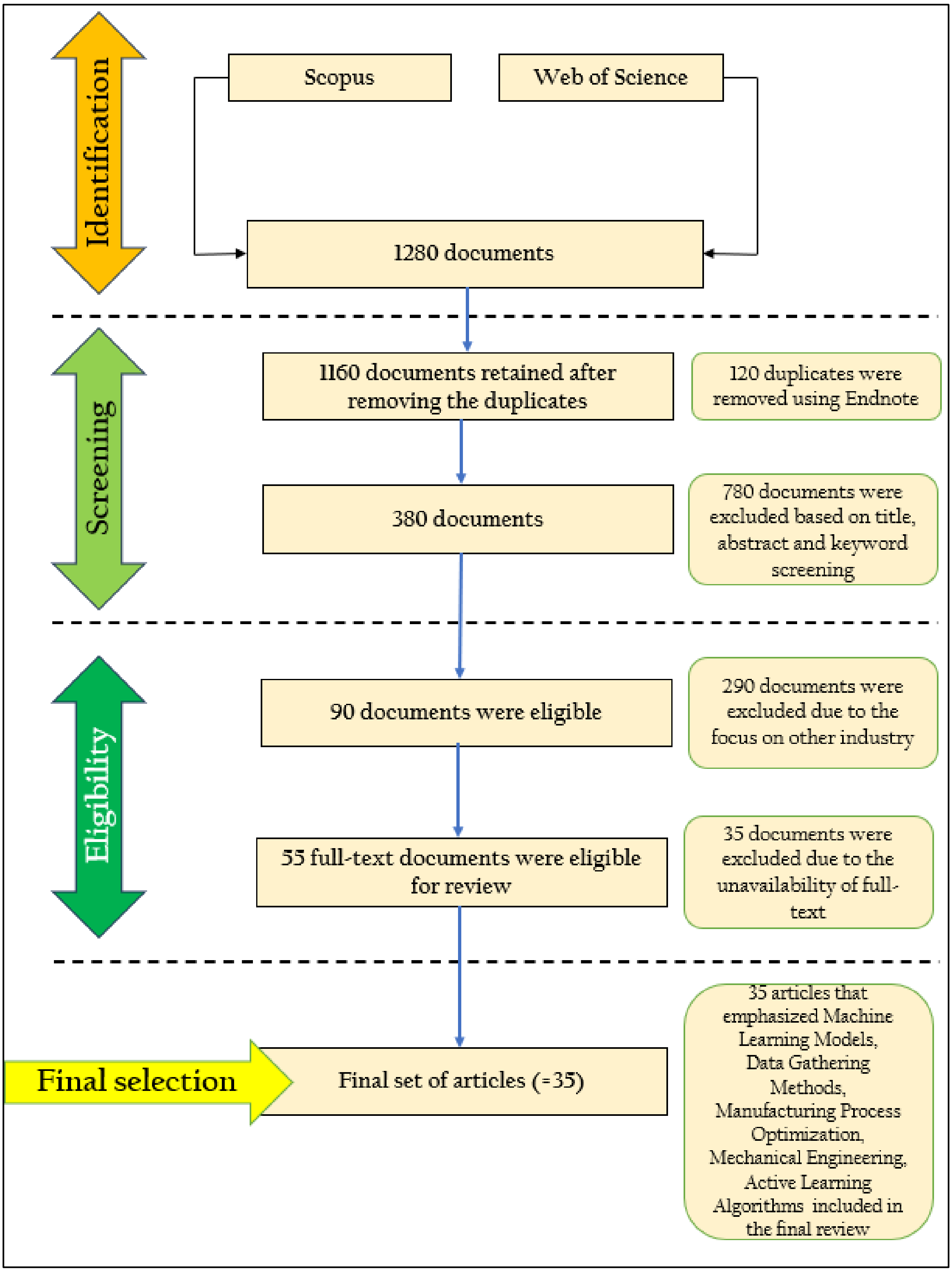
Figure 1: Flowchart for this study



Findings

The findings from the case studies underscore the effectiveness of the Design of Experiments (DOE) in traditional manufacturing environments. In Case Study 1, the DOE approach provided a robust framework for mapping the relationships between heat treatment parameters and resulting material properties, such as hardness and tensile strength (Kandar & Akil, 2016). The methodical exploration of variable interactions enabled by DOE was invaluable in identifying optimal process settings. However, this approach also highlighted the method's resource-intensive nature, as substantial experimental runs were necessary to cover the breadth of the variable space (da Silva & Zanini, 2004; Greenhill et al., 2020). This aspect of DOE underscores the need for substantial upfront planning and resource allocation to achieve comprehensive results. In contrast, Case Study 2 illustrated the advantages of Active Learning (AL) in data-driven environments, particularly in predictive maintenance applications within the aerospace industry. The AL model's capacity to make accurate predictions with fewer data points addressed the challenge of data scarcity and the prohibitive cost of data acquisition in such high-stakes environments (Alagumurthi et al., 2006; Lafifi et al., 2019). The AL approach was cost-effective and demonstrated rapid adaptability to new data, enhancing its predictive accuracy over time (Alemohammad & Shahini, 2010). This efficiency points to AL's potential to revolutionise data-gathering processes by focusing on the most informative data points.

The hybrid approach examined in Case Study 3, which combined DOE and AL, presented a novel pathway to harness the strengths of both methods. This approach utilised DOE to establish a broad understanding of the process variables and their effects, and AL refined the model by focusing on data points critical to the outcome (Hernández-de-Menéndez et al., 2019). The result was a significant improvement in the efficiency of the automotive manufacturing plant's robotic assembly line, with a notable reduction in defect rates. The success of this hybrid model indicates the potential for innovative approaches that integrate traditional and modern data-gathering techniques, yielding results that may not be achievable through either method alone. The implications of these findings for manufacturing process optimisation are substantial. The comparative effectiveness of DOE and AL highlights a strategic choice that manufacturers must make depending on the nature of the data, the complexity of the process, and the resources available. The insights from the case studies suggest that while DOE provides a thorough understanding of process variables, AL offers a pathway to operational efficiency through targeted data analysis. Moreover, the promising results from the hybrid approach point towards a future where the integration of various methods can lead to optimised manufacturing processes that are both efficient and adaptive to new data.

Discussion

The discussion of the findings from the systematic literature review and case studies analysis on data gathering methods in manufacturing and mechanical engineering, considering DOE and AL methodologies, is multilayered and reveals several insights. The case studies and associated literature underscore a critical comparison between the traditional DOE approaches and the emergent AL techniques. With its structured experimental design, DOE remains a robust framework for understanding the extensive interplay of variables in manufacturing processes. However, this method's requirement for many trials poses inherent challenges regarding time, cost, and resource allocation (Cho et al., 2021). On the other hand, AL methodologies demonstrate remarkable efficiency by requiring fewer data points to achieve comparable or superior predictive performance. This efficiency is particularly pronounced when data acquisition is costly or logistically challenging, such as aerospace applications (Cheng & Jin, 2021).

The practicality of implementing AL in real-world manufacturing scenarios is a subject of intense discussion. While AL shows potential in research environments, its scalability and integration into existing manufacturing systems are not yet fully understood (Wende et al., 2020). The effectiveness of AL depends significantly on the initial dataset's quality and the algorithm's capability to learn from new data inputs. This need for high-quality initial data sets can be a barrier to entry for some manufacturing contexts where data may be imperfect or incomplete (Bamberg et al., 2010). Integrating AL with other emerging technologies, such as IoT and digital twins, has been identified as a promising avenue for future research. Such integration could lead to more autonomous, self-improving manufacturing systems that can adapt to real-time changes. However, current research in this area is sparse, indicating a significant opportunity for future exploration (Christie & De Graaff, 2017). Moreover, as manufacturing environments become increasingly complex and data-driven, developing more sophisticated AL models to navigate this complexity will be crucial (Green & Thompson, 2023). For industry stakeholders, the strategic implications of choosing between DOE and AL or adopting a hybrid approach are profound. Decision-makers must weigh the trade-offs between the exhaustive but comprehensive nature of DOE and the targeted efficiency of AL. The findings from this review suggest that a nuanced approach, tailored to the specific requirements of the manufacturing process and the nature of the available data, is essential. In particular, the hybrid approach may offer a balanced strategy, leveraging the broad exploratory power of DOE and the focused efficiency of AL.

Conclusion

The systematic literature review and case study analysis undertaken in this research have provided a comprehensive overview of data-gathering methods in machine learning applications within manufacturing and mechanical engineering. The comparison between Design of Experiments (DOE) and Active Learning (AL) methodologies has highlighted each approach's unique strengths and limitations. DOE's structured and systematic exploration of experimental conditions has been reaffirmed as a cornerstone in traditional manufacturing settings, offering depth and clarity in understanding the impact of multiple variables. However, the advent of AL poses a transformative alternative, capable of streamlining the data-gathering process by focusing on the most informative data points, thereby promising significant reductions in time and resources required for model training.

The case studies have illuminated the practical implications of these methods, revealing that while AL can offer efficiencies in data usage and potentially improve predictive accuracy, it also comes with challenges related to integration into existing systems and reliance on the quality of initial data sets. The insights gained also suggest that a hybrid approach, leveraging the broad insights of DOE and the targeted efficiency of AL, could present a valuable strategy for specific manufacturing contexts. Looking ahead, it is evident that the field is ripe for further exploration, particularly in integrating AL with other cutting-edge technologies and developing more sophisticated AL models to handle the increasing complexity of manufacturing environments. For practitioners and scholars alike, the findings underscore the importance of selecting an appropriate data-gathering methodology that aligns with the specific requirements of the manufacturing process and the nature of the data available. As the manufacturing landscape continues to evolve, propelled by advancements in machine learning and data analysis, this research provides a foundation for informed decision-making and strategic planning. It encourages innovation and adaptation in data-gathering methods, ensuring manufacturing processes remain efficient, cost-effective, and at the forefront of technological advancement.

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