AI-Driven Comprehension of Autonomous Construction Equipment Behavior for Improved PSS Development

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Abstract

This paper presents an approach that utilizes artificial intelligence techniques to identify autonomous machine behavior patterns. The context for investigation involves a fleet of prototype autonomous haulers as part of a Product Service System solution under development in the construction and mining industry. The approach involves using deep learning-based object detection and computer vision to understand how prototype machines operate in different situations. The trained model accurately predicts and tracks the loaded and unloaded machines and helps to identify data patterns such as course deviations, machine failures, unexpected slowdowns, battery life, machine activity, number of cycles per charge, and speed. PSS solutions hinge on efficiently allocating resources to meet the required site-level output. Solution providers can make more informed decisions at the earlier stages of development by using the AI techniques outlined in the paper, considering asset management and reallocation of resources to account for unplanned stoppages or unexpected slowdowns. Understanding machine behavioral aspects in early-stage PSS development could enable more efficient and customized PSS solutions.

Keywords: Product-Service System, Deep Learning, Autonomous Machine, Prototyping, Machine Behavior.

1. Introduction

Rapid innovation in technology and globalization has significantly transformed the industrial approach to value creation. Consequently, organizations have transitioned from a product-centric to a more service-oriented mindset. This shift has resulted in what is known as “Product-Service Systems” (PSS) (Baines et al., 2009). In recent years, PSS development has been rapidly expanding, aiming to create effective strategies for more efficient and sustainable systems that meet customer needs and reduce the environmental foot-prints of the products (Fargnoli et al., 2018). The development of new products coupled with services operating within a new system presents significant challenges in managing solution space ambiguity. This is especially true for PSS development, which is a complex process that involves designing, prototyping, and testing to ensure that the final product provides an optimal user experience (Exner et al., 2015).

Furthermore, PSS development is a collaborative and interdisciplinary process that involves the integration of products and services in order to provide customers with a comprehensive solution. Effective collaboration between various stakeholders, such as designers, engineers, and marketers, is crucial for the success of PSS development (Isaksson et al., 2009). The rapid advancement of technology has led to the development of complex machines and systems that play a crucial role in various industries, such as construction, mining, and transportation. Nevertheless, comprehending the behavioral aspects of these complex systems of machines in different contexts and environments is essential to ensure their efficient operations and maintenance. This is particularly important in the context of PSS development, where the primary needs and requirements of the customers and other affiliated stakeholders must be identified early in the process to align the individual and system technical decisions throughout the process (Fargnoli et al., 2018; Kimita et al., 2015). The concept of machine behavior encompasses numerous elements, such as the

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machine's design, the operational environment, and interactions with other systems. Due to their complexity, machines can sometimes exhibit unpredictable behavior, which poses challenges for decision-makers to diagnose issues and make well-informed decisions (Grieves & Vickers, 2017).

In PSS design, prototyping has become an important approach that allows designers to test and refine their concepts in a representative context. Early-stage prototyping is particularly important for exploring and testing different concepts (R. M. Ruvald et al., 2021), which promotes active learning. Active learning is an integral part of this approach, facilitating the acquisition of new knowledge about the design space and relevant phenomena, and advancing designers' mental or analytical models of phenomenal interactions (Telenko et al., 2016). This process enables designers to rapidly iterate and refine their design concepts, gather information, and receive fast feedback. Prototypes serve as a flexible vehicle for exploring solutions and promoting communication across relevant disciplines throughout the PSS value chain (Exner et al., 2015). However, a clearer understanding of the relationship between representation and decision-making is necessary, as the value of information, contextual factors, and systems prototyping in developing prototypes remains relatively less explored. Designers can gain insights into a machine's behavior by creating a system prototype, leading to the development of more effective systems.

Integrating advanced technologies and industry 4.0 capabilities in traditional industries such as construction machinery and mining has led to the development of more tailored and efficient solutions (R. Ruvald et al., 2019). The introduction of artificial intelligence (AI) in PSS development has revolutionized machine design, operation, and maintenance. AI techniques, including deep learning and computer vision, have become powerful tools for analyzing machine behavior in PSS development. With the ability to capture, process, and analyze vast amounts of data, these technologies provide insights into machine behavior that were previously inaccessible (Abioye et al., 2021). Additionally, the vast amount of data generated adds to the complexity, uncertainty, and ambiguity of the decision-making process. Therefore, it is essential to have a concentrated pool of knowledge to effectively operate the transition toward PSS and generate innovation while communicating it efficiently to relevant stakeholders (R. Ruvald et al., 2019).

To support informed decision-making in early-stage PSS development, this paper focuses on utilizing AI techniques to identify patterns of machines' behavior in a simulated prototyping environment. The research hypothesis guiding this study is that by employing AI techniques in a simulated prototyping environment, decision-makers can gain valuable insights into machine behavior, enabling informed decisions and improved PSS development outcomes.

This paper is structured as follows: In section two, the relevant literature on the application of digital technologies in PSS development is presented. Section three describes the research approach utilized in this study. Section four presents the applied research methodology. Section five provides the results of our experiments, including the decision support system. Finally, section six concludes the paper and discusses the implications of our research findings for PSS development.

2. Literature Review

Products and services are often combined to provide maximum value for both users and providers. This bundling may also involve novel digital technologies, leading to the creation of smart product-service systems (Chowdhury et al., 2018) or digital-enabled PSS (Tukker, 2015). Remote monitoring of these systems using digital technologies has been discussed in the literature (Andersson & Mattsson, 2015; Jonsson et al., 2008). However, there is a need to understand how the adoption of digital technologies into the business model affects wider organizational changes (Grubic, 2014), particularly within the context of PSS development in the construction and mining industry.

In the early stages of product design, concept evaluations have a significant impact on the final value of the product due to the vast design solution space (Boukhris et al., 2017). However, in the early stages decision-making is characterized by ambiguity and, limited knowledge about the problem or solution. To address this uncertainty, the design thinking framework suggests using prototypes as a useful approach (Brown, 2008). Traditional prototyping approaches prescribe building full scale physical models of products or services to assess risk prior to manufacturing, which can be considered too late, time-consuming and/or costly an activity to adequately represent the final product or service. Alternatively, experience prototyping, which can be conducted prior to full scale manufacturing described above, involves creatively constructing immersive experiences blending various prototypes and simulated environments that allow potential customers to interact with the future product and/or service solution (Buchenau & Suri, 2000).

Recent years have witnessed a growing interest in the use of AI techniques, particularly in object detection and tracking. Advancements in computer vision-based approaches have made visual information more accessible through object recognition (Zientara et al., 2017). However, challenges remain in automatic scene understanding from video streams and 3D reconstruction, as factors such as motion blur, image resolution, noise, lighting changes, scale, and orientation can impact the accuracy of existing systems (Saha et al., 2019).

The integration of AI techniques in PSS development has paved the way for novel business models and improved customer experience, fostering the growth of AI-driven PSS solutions (Nicoletti & Appolloni, 2023; Walk et al., 2023). Several studies highlight the impact of AI in PSS developments through decision-making frameworks (Aeddula et al., 2021; Wall et al., 2020) and optimizing service offerings (Sala et al., 2021). In the construction industry, data-driven design frameworks are transforming the way products are conceptualized, paving the way for service innovation strategies. Additionally, AI techniques are unlocking insights from usage data, customer feedbacks, and maintenance reports, driving proactive service enhancements, facilitating effective PSS design (Chen et al., 2019; Dickens et al., 2023; Sala et al., 2022). However, the integration of AI with PSS comes with the limitations and challenges associated with the data during the development process (Exner et al., 2017).

To address these challenges, researchers have proposed interactive and hybrid approaches that involve collaboration between humans and AI systems. In this context, low-fidelity prototypes have been developed to understand the challenges in human-AI interaction, particularly in remote-sighted assistance services (Xie et al., 2022). However, within the context of PSS development in the construction and mining industry, there is a knowledge gap in the literature regarding the value of bundling together system prototyping and AI techniques in early-stage PSS development. Further exploration of the benefits, challenges, and potential applications of hybrid approaches, which combine human expertise with AI capabilities, could provide valuable insights into the development of PSS in the construction and mining industry. By attempting to address this gap and building upon the existing literature, this research aims to contribute to a deeper understanding of the intersection between digital technologies, prototypes, and AI techniques in the context of PSS development in the construction and mining industry.

3. Research Approach

This paper adopts a prescriptive research approach within the framework of the design research methodology (Blessing & Chakrabarti, 2009). The prescriptive research approach aims to provide practical guidelines, recommendations, or interventions to address specific design challenges and improve the development process (Blessing & Chakrabarti, 2009). In this study, the prescriptive research approach aligns with the goal of enhancing PSS development by incorporating additional features and capabilities based on insights gained from a previous case study (R. Ruvald et al., 2018).

Building on the findings of the previous case study, which focused on the design of data-driven PSS using early-stage system prototyping (R. Ruvald et al., 2018), this research aimed to expand upon the existing framework and incorporate specific features and capabilities. These additions were intended to address identified limitations and gaps in PSS development.

To achieve this, image and sensor data were collected during scaled prototype machine operations to create a comprehensive dataset for training and analysis purposes. The dataset served as a foundation for incorporating additional features and capabilities into the PSS development process. These specific additions were carefully selected based on insights gained from the previous case study, taking into consideration the unique requirements and challenges of the construction and mining industry.

By incorporating these features and capabilities, the research seeks to enhance PSS development by improving the accuracy of machine behavior analysis, facilitating informed decision-making, and enabling the creation of more efficient and sustainable systems. Additionally, the additions aim to address previously identified limitations and gaps, ensuring that the PSS development process is more comprehensive, robust, and aligned with the needs of both users and providers.

Through the utilization of the prescriptive research approach and the incorporation of specific features and capabilities, this research aims to contribute to the advancement of PSS development in the construction and mining industry, providing practical insights and recommendations for researchers and practitioners in the field.

Research Question: How can AI techniques be utilized in a simulated prototyping environment to comprehend the behavioral aspects of machines and enhance the development of product-service systems?

Research Objective: The research objective of this study is to investigate the effectiveness of utilizing AI techniques, such as deep learning-based object detection and tracking, in comprehending machine behavior and optimizing PSS development.

4. Materials and Method

4.1. Prototype

The prototype platform utilized in this study consisted of a scaled-down site measuring 5m x 5m, simulating the environment of a quarry or mining operation. The key component of the platform was the inclusion of two autonomous haulers engaged in loading and dumping interactions, replicating typical operations. To enable an autonomous experience for the user, the haulers were equipped with a range of sensors, control boards, and communication devices. Further information on the specifications and technical details of the prototype platform can be found at (PDRL, 2019.)

Figure 1. Scaled-down site.

4.2. Deep Learning

In this study, deep learning techniques were utilized to address complex problems characterized by intricate patterns or high-dimensional data by leveraging artificial neural networks, which are a fundamental component of deep learning algorithms. In the context of computer vision, deep learning techniques have demonstrated success in various domains, including object detection and tracking. The workflow adopted in this study involved the utilization of the YOLOV5 model for object detection and the kernelized correlation filter (KCF) algorithm for object tracking.

4.2.1. Dataset: The case study involved a custom machine prototype utilized for detection and tracking, as described in Section 5. The dataset employed in this study encompassed a diverse collection of images capturing the prototype under different conditions, such as variations in brightness, scale, and orientation. A total of 959 images were manually labeled to create the dataset. The manual labeling process involved annotating the images to identify and outline the presence of the machine prototype. Figure 2 represents the data samples from the dataset.

Figure 2. Data samples from the dataset.

4.2.2. YOLOv5: The YOLOv5 model, known for its real-time object detection capabilities, was selected for this study. YOLO, which stands for "You Only Look Once," utilizes a single neural network to detect objects in images or video streams, achieving high accuracy and real-time performance (Redmon et al., 2016). In this study, the YOLOv5 framework, built on the PyTorch machine learning library, was employed. To optimize its performance for the specific requirements of the study, configurations, and modifications were made to the YOLOv5 model. These adaptations included adjustments to the training process, selection of appropriate hyperparameters, and potential modifications to the model architecture (Redmon et al., 2016).

4.2.3. Object Detection: The trained YOLOv5 model detects the machine prototype in real time using a standard camera. Typically, the object detection algorithm analyses only the spatial features within an individual frame while disregarding the inter-frame relationships, leading to a relatively slow performance (Zhou et al., 2022).

4.2.4. Kernelized Correlation Filter: To address the issues of the individual frame leading to missed detection and drifting, a visual object tracking method was employed. KCF is a popular algorithm used for visual object tracking in computer vision applications. It has gained popularity due to its high speed and accuracy in video-tracking objects. One of the main reasons why KCF is preferred over other algorithms is its ability to learn the appearance of an object in the video and then use that learned model to track the object in subsequent frames. KCF uses correlation filters to learn the object's appearance, which allows it to track the object even when it undergoes deformations, changes in illumination, or partial occlusions (Henriques et al., 2015).

By incorporating the prototype platform and employing deep learning techniques, including the YOLOv5 model and Kernelized Correlation Filter algorithm, this study aimed to analyze machine behavior and track objects in real-time within the simulated prototyping environment. The integration of these methodologies facilitated the collection of valuable data for subsequent analysis and provided insights into the performance and potential improvements of the proposed PSS development approach.

5. Results

To comprehend the machines' behavior within the simulated prototyping environment, a deep learning-based workflow was employed. A simulated prototyping environment process is presented in Figure 1 with two machines being the focus of the study to understand their behavior in the overall simulated site scenario.

Figure 3. Multiple machines detection.

The workflow involved training the YOLOv5 model on a custom dataset and conducting real-time validation using a standard web camera. The trained model successfully detected multiple custom machines, as depicted in Figure 3. The accuracy of the object detection model is 98.52%.

Furthermore, to achieve a comprehensive understanding of the machine interactions, the tracking system simultaneously monitored two machines. Figure 4a and Figure 4b illustrates this process, with machines color-coded as green and red for visualization purposes. Green represents a loaded machine headed to the dumping site, while red signifies a machine headed to the loading site, respectively. This color-coded scheme not only aids in real-time tracking but also streamlines the identification of each machine on the site track.

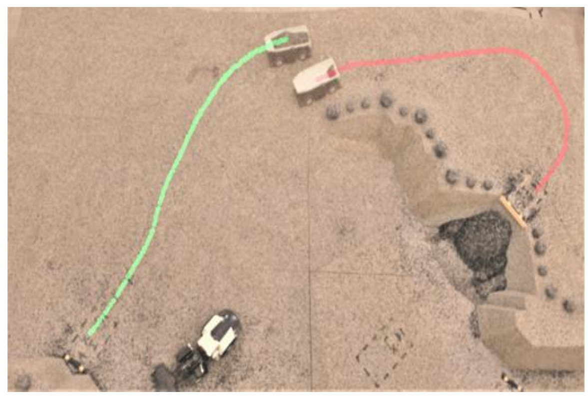

Figure 4a. Machines tracking.

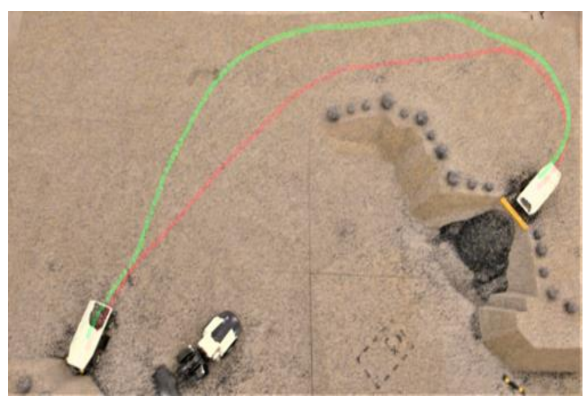

Figure 4b. Machines tracking

A decision support system was developed to enable human-machine interactions, and Figure 5 shows the human-machine interface presenting collected information for an informed decision-making process. The interface provides real-time information for all machines in the simulated site, allowing decision-makers to select the desired machine information. Additionally, the interface includes an emergency stop function to pause the entire machine fleet operations in case of any unexpected occurrences.

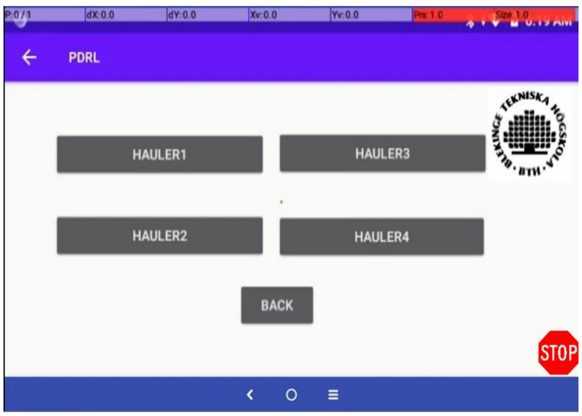

Figure 5. Human-machine interface

The human-machine interface provides real-time information for all the focused machines in the simulated site, including battery life, speed, activity, and cycles, with an emergency stop function available for individual machines, as shown in Figure 6a and battery life of the machines in Figure 6b (for visualization purpose, both the machines' data is shown in a single plot).

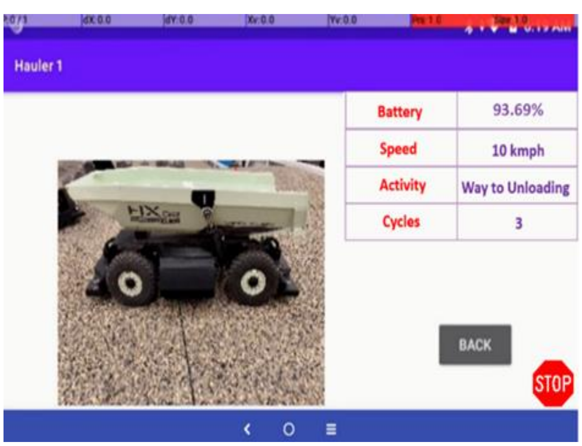

Figure 6a. Individual machine data

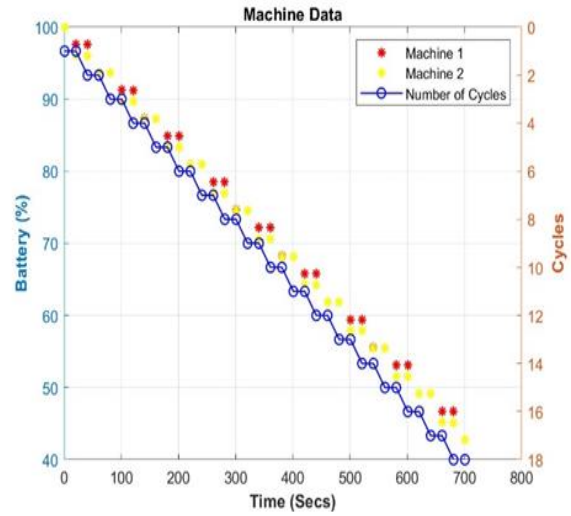

Figure 6b. Machines' data

The simultaneous localization and mapping of the machines were used with the KCF method to identify their activity from real-time video. To ensure seamless operation, the human-machine interface was designed to alert users in case of machine breakdown and remind them to charge the batteries when the battery level goes below 35%. Figure 7a illustrates the interface system with a warning sign indicator for a breakdown machine and visualization of the machine breakdown in the simulated environment is show in Figure 7b.

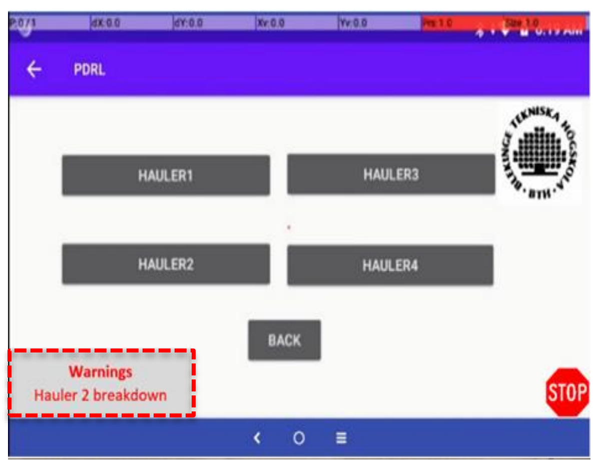

Figure 7a. Interface warning of machine breakdown

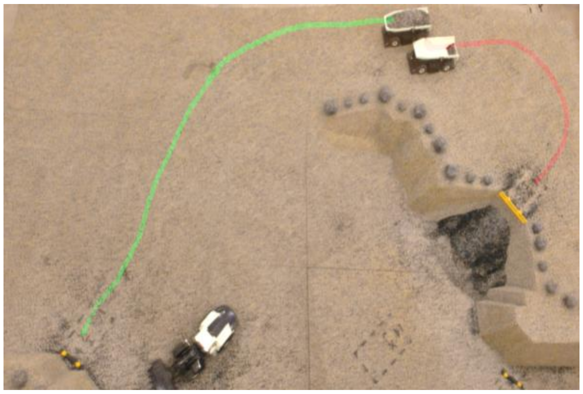

Figure 7b. Visualization of machine breakdown (Red Line).

5.1. Validation

In terms of evaluation metrics, Multiple Object Tracking Accuracy (MOTA) was utilized to assess the tracking performance. It is a widely recognized evaluation metric employed to assess the performance of multiple object tracking. It provides a comprehensive measure of tracking accuracy by considering various aspects, including false positives (FP), false negatives (FN), misses and identity switches (IDSW), and total count of ground truth objects (GT) at a specific time t. The ground truth values were manually annotated, ensuring precise labeling of objects. It is a measure of the accuracy of the model and is defined according to (Bernardin & Stiefelhagen, 2008).

$$MOTA = 1 - \frac{\sum(FN+FP+IDSW)_t}{\sum GT_t} \qquad (1)$$

A higher MOTA value indicates better tracking performance, as it signifies a lower number of errors and higher accuracy in tracking the objects. A MOTA value of 1 indicates perfect tracking with no errors. In this research case of two-object detection and tracking scenario, the model demonstrated an accuracy of 96.59%.

Intentional breakdown of a particular machine is represented in Figure 7a and 7b validates the functionality of the decision support system service. The prototype interface and visualizations were deployed with the functional scale site at three separate events in USA, India, and China. At these events observers were allowed to interact with the machines and interfaces as a form of engagement. The observers at these events ranged from potential customers to other interested industry professionals. The overall response was positive to the prototype and enabled dialogue with potential users on the overall system as well as machine level specifics. This type of feedback is vital from a PSS development perspective because it allows contextualized feedback from highly relevant stakeholders enabling the potential optimization of technical details within the complex socio-technical requirements existing in an overall PSS solution.

By incorporating the deep learning-based workflow, developing the decision support system, and achieving a high MOTA accuracy, this research provides valuable insights into understanding and monitoring the behavior of machines within the simulated site and provides the foundations for informed decision-making in early-stage PSS development.

6. Discussions and Conclusions

The research presented in this paper focuses on the utilization of AI techniques to gain valuable insights into the behavior of machines in PSS development. By employing deep learning and computer vision, AI techniques enable the identification of data patterns, providing a more detailed understanding of machine behavior. The training of a deep learning based YOLOv5 model on a custom dataset enables the detection of machines, while the KCF method facilitates accurate tracking of loaded and unloaded machines in a simulated site environment.

One of the key findings of this research is the ability of AI techniques to identify patterns in machine behavior. This capability offers valuable insights that can inform decision-making in early-stage PSS development. By comprehending machine behavior, decision-makers can make informed decisions that enhance operational efficiency. For example, machine detection and tracking allow for the identification of potential maintenance needs and the development of predictive maintenance strategies. This not only reduces maintenance costs but also extends the lifespan of machines, resulting in improved asset management and cost savings (Poór & Basl, 2019).

Understanding data patterns plays a crucial role in understanding machine behavior in various scenarios, such as course tracking, machine failure, unexpected slowdowns, battery life, speed, cycles per charge, and machine activity. This understanding supports informed decision-making during PSS development concerning potential alternatives to manage hauler/machine assets and reallocate resources towards achieving targeted operational efficiency. By analyzing the available data, decision-makers can identify potential risk areas and develop contingency plans to minimize the impact of unplanned events.

Machine detection and tracking contribute to the understanding of machine behavior, facilitating the identification of maintenance requirements and ensuring the machines adhere to designated paths, thereby ensuring human safety. The human-machine interaction, facilitated by the developed interface, allows for real-time observation of machine behavior, including battery life, speed, and charging needs, as well as the detection of potential obstacles and machine breakdowns. Visualizations aid in identifying breakdowns or issues in machine behavior, while the emergency stop function ensures operational safety in the face of unexpected catastrophic occurrences. Furthermore, the comparison of battery usage per cycle between individual machines provides valuable insights for optimized resource allocation.

Furthermore, the utilization of AI techniques could enable plans for strategizing around optimal resource allocation to be considered during the early stages of PSS development. Decision-makers can leverage the insights gained from machine behavior to efficiently anticipate and react to potential issues requiring the reallocation of resources, minimizing downtime, and maximizing productivity. By understanding patterns such as unexpected slowdowns or battery usage, decision-makers have a better understanding of how to compensate for the missing capacity, ensuring operational efficiency.

The findings of this research could have broader implications for PSS development beyond the simulated prototyping environment. The insights gained through the usage of AI techniques can be applied to the development of full-scale PSS operations, where the optimization of operational efficiency and resource allocation is of critical importance. By incorporating AI techniques in the operational phase, decision-makers can further enhance, customise, or streamline PSS outcomes to deliver increased value to the customers.

The significance of this research lies in its potential to advance the field of PSS development and contribute to the body of knowledge on the application of AI techniques. By comprehending machine behavior using AI techniques in a simulated prototyping environment, decision-makers can optimize operational efficiency, minimize downtime, improve asset management, and enhance resource allocation. Additionally, a deeper understanding of machine behavior can enable predictive maintenance strategies, reducing maintenance costs and extending machine lifespan. The research's influence extends to the PSS development process, particularly in the traditional industries like construction and mining. By exploring the role of advanced technologies, it sheds light on their capacity to accelerate the design and testing phases of PSS development.

In conclusion, this research has demonstrated the effectiveness of utilizing AI techniques to identify patterns of machines' behavior in early-stage PSS development. The insights gained from these techniques enable decision-makers to make informed decisions that optimize operational efficiency, improve asset management, and enhance resource allocation. By comprehending machine behavior using AI techniques, PSS developers can minimize downtime, reduce maintenance costs, extend machine lifespan, and allocate resources more effectively.

Limitations: The research was conducted within a controlled environment, and as a result, the behavior of machines in different conditions, such as rain or snow, was not considered. Additionally, it is important to note that the human-machine interface was presented with basic functionalities for demonstration purposes.

7. Future Works

Future research will involve investigating the behavior of machines in various controlled environments and exploring the relationships between different machines, such as interactions between wheel loaders and haulers or between two haulers. In addition, the tracking of all sorts of items on a job site (tools, humans, and other machines). Furthermore, the application of this prototyping process within PSS development can be explored deeper as a means through which to gather data at multiple levels of the conceptual system, including the impact on roles, responsibilities, and decision-making processes within interdisciplinary teams, to drive critical design decisions. Lastly, the potential utilization of in-built camera sensors in machines and the subsequent analysis of machine behavior can lead to including operator in the loop design methods for training the machine pathing and predictive maintenance models.

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