

Improving Manufacturing Product–Service Systems through Predictive Maintenance

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Abstract

Product Service Systems includes the operation of machinery with maintenance, repairs and other services related. There are several components available in the machines which can be categorized into consumer, industrial products and services. Total predictive maintenance is a method for maintaining and improving the durability of production and quality systems. This leading to overall equipment effectiveness and elimination of waste through lean processes. The research presents a model integrating product service systems, total productive maintenance and overall equipment effectiveness. A tier one rail company chosen as case study to solve maintenance problems on the operational and maintenance problems. Some of the common problems associated with the machines include bearing failure, flange damage, structural fatigue, component malfunction, degradation or wear and system malfunction. It is not all technologies that are relevant to the problems in machines although some can be adapted to solve the problems. Therefore, a need to examine which technologies can be integrated into the machinery arises. The extended usage of machines during production requires managing of the machine fleet leveraging technology to help manufacturers, suppliers, maintenance technicians and the entire value chain to be established for manufacturing and assembled components. This is part of sustainable development goals number nine (9), which is to build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation. The results present improvement and future work for the proposed model.

Keywords

Product service systems, Total productive maintenance, Overall equipment effectiveness, Lean manufacturing and Rail transport.

1. Introduction

Manufacturing consists of suppliers and service providers that assemble and design products forming the backbone of most of the world's economies. Manufacturing ensures the delivery of goods and services at various stages of the value chain. The industry is undergoing a transformation driven by new technologies, which looks very promising because it will allow agriculture and manufacturing sector to increase productivity and profitability (Baiming & Voskerichyan, 2024). The paper addresses integration of product service system, total productive maintenance and overall equipment effectiveness in the rail sector. The production environment requires regular monitoring of equipment and lean operations to improve. Modern systems pose significant challenges for maintenance management, as traditional life-cycle maintenance schemes have reached their limits for flexibly managed systems. Innovative approaches to data-driven predictive maintenance have been developed but fall far short of industry standards in an industry that tends to stick to proven, traditional techniques.

Total productivity maintenance strategies work to improve accuracy of equipment failure lifespan prediction models. The use of sensor technologies can address many areas of production such as component monitoring, detecting vibrations on machines, cable theft, infrastructure damage and machine fleet management. The tier one rail company's assembly process involves housing the motor, gearbox, pneumatics connection area, braking unit and speed sensors. Condition monitoring of motors, fans, pumps, gearboxes, turbines, etc., especially bearings and internal gears, plays an important role in the maintenance program of rotating machinery. This refers to a combination of datasets, temperature, vibration, volume, speed, and variety. The proposed model combines lean practices, overall equipment effectiveness and Total productive maintenance to improve the bundle of products service. Physical assets in industrial manufacturing are equipped with smart sensors, which connect them to the internet and create a networked physical system. This model is applied to research fields such as smart environments, healthcare and logistics. Beyond these applications, Industrial Product Service Systems provide a wide range of benefits to the manufacturing industry by enabling more efficient monitoring, control and optimization in a cost-effective manner. A manufacturing company was selected to examine its product service system leanness levels. The degree of lean adoption in the service offerings process is investigated with the goal of optimization. Managers and maintenance technicians can use the model to examine the leanness of their service offering (Elnadi & Shehab, 2021). Conceptual models can play a major role in helping us understand the impact of Total Productive Maintenance 4.0 on manufacturing. The results from application in the Indian manufacturing industry show positive impact when integration is done to increase dynamic capability. These are new business models which contribute towards the future viability and sustainability of a manufacturing company (Samadhiya et al., 2023).

(Elnadi & Shehab, 2015) explored the main enablers of successfully implementing lean principles within a product services system. The case study was focus on the United Kingdom manufacturing companies where various managers were interviewed. It is found that management status, work process, customer relationship, employee status and supplier relationship were the main enablers. In future work, research will need to be conducted on the actual implementation of lean practices in Industrial Product Service System. In train maintenance planning total productive maintenance, product service system and overall equipment effectiveness results in new maintenance services, increased availability and cost reduction in operational efficiency. The goal is to have an integrated method for value creation with sensors, operational data and maintenance planning we can detect signs of failure and intervene before accidents can occur.

2. Literature Review

Smart factories are a concept which came with industry 4.0 using the latest technology to improve production leading to increased optimization and optimized production processes. The results present applications of artificial intelligence through different lifecycle stages of industrial equipment. The design phase has adopted generative adversarial networks and deep learning amongst eighteen (18) identified artificial techniques. In the manufacturing phase twenty-nine techniques were identified as being active in the sector including support vector machine, artificial neural networks and general algorithm. Thirty-six (36) different AI techniques were identified for fault diagnosis, root cause analysis and prognosis of components in the maintenance sector. Support vector machine, artificial neural networks, long short-term memory, variants and autoencoder are most commonly used for component prognosis and fault

diagnosis (Elahi et al., 2023). Research was conducted to explore artificial intelligence in manufacturing, focusing on equipment through life cycle stages. Forty-two articles were selected for a specified period reviewing AI techniques applied in manufacturing. The review identifies applications for techniques such as support vector machines, neural networks, Bayesian networks.

A study was conducted in a manufacturing environment to predict the remaining useful life of production lines in a plant. Sensors were utilised to collect data required in the factory using machine learning models in real time to organise and analyse trends. The following methods were used to develop the model: machine learning algorithm, random forest, xgboost, multilayer perception and vector regression. Random forest and xgboost models showed the best performance in predicting failures on the production lines. The results were forty-two (42) percent of failures being predicted and prevented (Taşcı et al., 2023). Rosati et al 2022 (Rosati et al., 2022) introduce a decision support system for the predictive maintenance challenge of data type used to predict remaining useful life focusing on a real industrial case. The use case originated from a manufacturing company's machine centre, operating a flexible manufacturing system with a focus on two robot loading parts. The decision support system integrates feature extraction with machine learning algorithm utilising message queuing telemetry transport to collect data. A trapezoidal numerical integration is performed for feature extraction. The random forest regression model was applied for remaining useful life predictions. Storage was created using Azure Blob as a cloud architecture. The decision support system demonstrated to be a good platform for integration between predictive maintenance, machine learning and interpretability.

Corrective and predictive maintenance philosophies have evolved over the past year due to emerging technologies related to industry 4.0. A review was conducted in power generation, issues addressed are common to other industries. The research presents practices and methodologies used by engineers in maintenance assets, pointing direction for further development (Mołęda et al., 2023). A review was conducted to evaluate the effectiveness of condition monitoring and predictive maintenance in industrial machines. Equipment in the plant requires real time monitoring for failures leading to reduction in high costs, unplanned downtime and safety. The quantitative analysis was conducted in the following application: industrial compressors, cable systems, frame work for remaining useful life, hydraulic pump condition monitoring, bearing fault diagnosis and conveyor belt system systems. The results presented show predictive maintenance is aligning with the key principles of industry 5.0 to promote more sustainable and human centred technologies (Garcia et al., 2025).

The development of digital twin has contributed to the advancement of predictive maintenance. A simulated maintenance system on a digital twin optimizes equipment remaining useful life, schedules, profitability, fault detection and machine availability. This research investigates applications for machine learning in a digital twin for predictive maintenance. A digital twin and predictive maintenance framework integrating the three methodologies was developed (Chen et al., 2023). Shahin et al 2023 (Shahin et al., 2023) report on two (20) early failure detection models to help avoid future breakdowns in equipment. The following methods were selected: deep learning, deep hybrid learning and machine learning. Further research suggested technicians and engineers can use the models to improve production and connection of lean manufacturing to maintenance. Corrective maintenance aligns poorly with lean due to its reactive approach, repairing equipment after failure. The results stated deep forest and gradient boosting with ninety percent accuracy being the highest.

Renewable energy systems have become critical to support the rapid advancement in industries, climate change and sustainable development. The usage of alternative energy sources demands much better maintenance philosophies for efficiency. The study expands on the application of artificial intelligence in energy and maintenance employing different machine learning and neural networks algorithms to develop predictive models. The case study is based on a wind farm solar installation and hydro-electric plants. The results demonstrated that artificial intelligence algorithm can predict equipment failure with ninety two percent (92%) accuracy reducing unplanned downtime by eight percent (8.5%) (Sakiru Folarin Bello et al., 2024).

2. Research Gap Analysis

In the context of train fleet maintenance planning, PSS can be used to optimize maintenance processes and improve overall train fleet performance. Sensors can be attached to trains to collect data about the condition of train components and use it to plan preventative maintenance tasks. A product service system in train maintenance planning leads to more efficient and effective maintenance processes, customized maintenance services, improved rolling stock reliability and availability, and reduced costs for train operators. It is important to look at each individual component

within the train system and determine the remaining useful life estimation service using dynamic dashboard application designed for reusability. Product Service Systems as a key component in various data science related research projects and can be applied to many IoT scenarios, such as smart cities, transportation and healthcare. It is continuously improved and new features are added on a regular basis. The product service system bundles the bogie physical subsystem with value-added services for maintenance, monitoring and diagnostics. This improves maintenance efficiency, reduces downtime, and optimizes resource allocation. Internet of Things technology can provide efficient connectivity solutions for a variety of use cases, both large-scale and critical IoT. Some of the most important requirements when considering large-scale deployments of these services include low deployment costs and long battery life. Low device cost, extended coverage area, support for many connected devices (extensibility), and security and privacy. The smart service canvas helps us select relevant sensors for data collection. When developing a methodology, it is also important to consider industry-specific standards and regulations related to vehicle maintenance. Lack of prior research studies on the topic which was a challenge in understanding the research problem being investigated. The lack of research in the area of TPM-PSS integration can lead to the development of a framework which will be used in the manufacturing sector.

3. Methods

This study integrates Product Service Systems, Lean principles and Total Productive Maintenance to improve equipment lifespan in a manufacturing environment. The benefits of having this model is reducing downtime and improving asset lifecycle performance. The collection of important bogie fleet data, historical maintenance records, including component information, working conditions, and performance metrics. This data will form the basis of our research. The collected data must be analysed to determine the maintenance needs of each component. Consider factors such as recommended maintenance activities, component life, and failure rates. We want to determine the performance, availability and reliability of our trains, which in turn determines the level of service. The railcar service sector is dominated by the industrial components needed to manufacture and assemble trains, such as heavy equipment, electrical equipment, computers and tools. Product-service systems in train bogie fleet and maintenance planning can lead to improvement and cost saving for the organization. Data analytics play a major role when an organization has to manage a large fleet of trains with big data to track component degradation and conditioned based maintenance. To identify planning needs and requirements, products are broken down into core elements of data collection in terms of their life cycle. Intelligent integration is possible thanks to the innovative direction of product and service elements. Data is collected during installation and sensors are incorporated into the product and converted into useful information. The data will be transformed through the development of a transversal platform allows iOS and Android to use (Figure 1 and Figure 2).

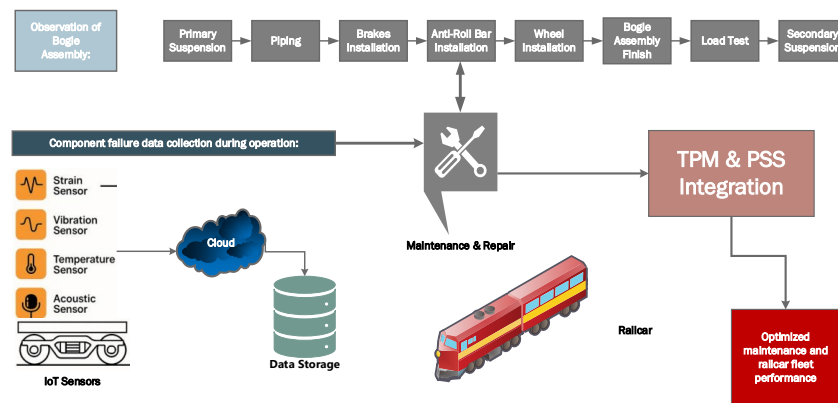


Figure 1. Process for engaging tier one rail company

Total Productive Maintenance works well with result-oriented Product Service System. The research data collection is done on the bogie assembly line, failure data documentation and maintenance/repair centre. This will be done through a transparent and informed process to minimise disruption. A walk about the assembly line helps us observe work that goes into completion of the bogie. The managers and engineers can help us access relevant documentation about major failures. To help us understand the repair process, depot & repair centre walk about will be required. Important historical documents for the study includes Bogie Failures records, Safety accidents, High life cycle cost

and Maintenance philosophy. This study depends on having access to the folks at the organizations, or documents and for that reason, access is denied or otherwise restricted. Factoring in non-disclosure forms and preparing participants could be a solution. Preventative maintenance within the pillars of Total Productive Maintenance can improve early equipment management leading to safer and healthier work environments. This concept of innovating using types of Product Service Systems and pillars of Total Productive Maintenance results in services that can help companies increase production volumes and maintenance (Hardt et al., 2021). The integration of lean principles with industrial product service systems helps companies implements servitization at different levels in the organization. This has led to the development of a product service leanness assessment model evaluating service levels in manufacturing. This model is built on three foundations criteria, enablers and attributes (Elnadi, 2015). There is still a gap in research to design more integrated solutions for the production environment. By combining PSS techniques, lean and Total Productive maintenance we close this gap and contribute to the body of knowledge.

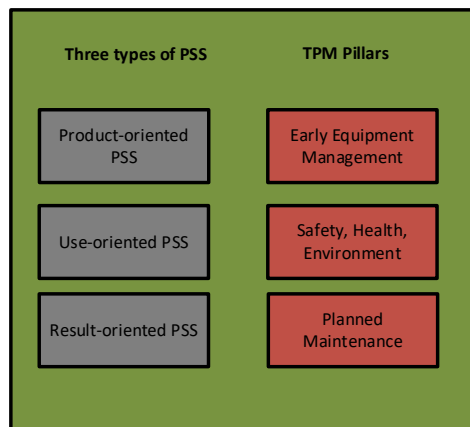


Figure 2. Types of PSS and pillars of TPM

Kusiak et al 2023 (Kusiak, 2023) introduce a framework to guide developments in prediction technology in a manufacturing environment. Eight areas namely scheduling, planning, decision, production demand prediction, quality prediction, process control, fault prediction and condition monitoring of application were explored with the goal of digitalizing manufacturing. The findings showed that within the eight areas there is increasing research on digital manufacturing. Observed challenges and barriers to future development were identified. The objective is to plan for value creation in the railcar bogie with product service integration.

The textile industry uses spinning machines especially in fabric production, recent advancement has contributed to the evolving of artificial yarn machines. Maintenance of the machinery becomes critical to ensure efficient production. Predictive maintenance integrated with machine learning methods provides an optimized maintenance strategy. The research outlines the establishment of a predictive maintenance system designed for yarn production using four machine learning and deep learning algorithm. The algorithms were further tested on other industrial machines and can be monitored on ThingsSpeak™ IoT interface. The experiment results show significant improvements in prediction accuracy (Akyaz & Engin, 2024). A preventative-conditioned based maintenance platform will be development to monitor the failures and increase safety of the railcar bogies.

Machinery and Equipment in the oil and gas industry is monitored through sensors, identifying patterns and irregular activity which can cause breakdowns of equipment. There are numerous problems in the production of oil and gas, including unplanned downtime, high production costs and equipment failures. Adoption of predictive maintenance strategies has become key to ensuring availability of equipment. Machine learning integration with predictive maintenance has transformed the oil and gas industry improving the lifespan of critical assets. Organizations in the oil and gas industry are encouraged to adopt the machine learning in predictive maintenance for significant cost saving (Emmanuella Onyinye Nwulu et al., 2023).

The automotive industry is undergoing fundamental changes approach to assembly of vehicles starting with design, selection of machines and maintenance. The industry has several challenges including post covid-19 recovery, staff

reduction globally, temporary plant closures, disruptions on the production of components and parts. The research project outlines planet 2050 initiatives in the areas of high-speed vehicle manufacturing equipment with one of their goals to reduce emissions, fuel consumption and vehicle weight. Predictive analytics will play a major role in production, supply chain, equipment maintenance and quality assurance. The results demonstrate there is a foundation laid for new technologies to solve problems and aid in the development of electric vehicles in future (Syed, 2025). To run an efficient production line the following is required: equipment availability and accurate sensors for data collection. The research focuses on predictive maintenance platform which uses an artificial neural network model with sensor data input. A case company used the platform and results state the platform can be used as an entry level solution to enable data based predictive maintenance (Fordal et al., 2023). Agu et al 2024 (Edith Ebele Agu et al., 2024) compiled application case studies of predictive analytics in different industries. In the retail industry the tool has been useful in understanding consumer behaviour. Data is gathered through algorithm to study on individuals needs them sending personalised messages and offers. In retail predictive analytics supports managers in inventory management and demand forecasting ensures they have safe levels of stock. The healthcare sector predictive models are trained to predict when a patient is likely to develop certain conditions or diseases. Forecasting patient demand to help with planning for staff, bed capacity and equipment availability. The financial industry has applied predictiveness in credit risk assessment and fraud detection. The manufacturing industry has undergone rapid changes due to the introduction of predictive analytics in maintenance of equipment and supply chain optimization. The various application of predictive analytics demonstrates flexibility of application in almost every industry to improve resource allocation, decision making and streamlining workflows.

The increasing volumes of vending machines in the public and commercial space is evident with some machines left nonfunctional due to outdated maintenance methods. This research presents a predictive maintenance framework specific for vending machines combining machine learning and sensor data. The machine is monitored in real time for component wear and forecasts are done to determine time for failure. This helps maintenance technicians with scheduling, extending equipment lifespan and eliminating downtime. Results show accelerated early fault detection and reduced service disruptions showing predictive maintenance integrated into vending infrastructure improves machine efficiency and service availability (Hasan, 2025). Forecasting as a tool has helped many organisations with their planning and meeting demand at peak times. In a production environment forecasting supports with inventory management, production output, equipment maintenance and market trends. A literature review was conducted on time series forecasting algorithms for industrial manufacturing systems. Time series forecasting models and their applications in different industries are examined. Hybrid models are shown to be more accurate and robust forecast (Fatima et al., 2024).

The food industry faces challenges of data security, ethical concerns and high production costs. Zatu et al 2024 (Zatsu et al., 2024) discuss the impact of artificial intelligence transformed systems in the food production. Artificial intelligence application in food science is in sensors, production, supply chain and nutrition. A review of how AI models contribute to improve predictive maintenance and related areas in this sector is presented. Some of the areas AI is playing a role are intelligent labels, shelf-life optimization, robotic packaging, inventory management and marketing. Artificial intelligence has emerged as a powerful tool for resource conservation and energy reduction the food industry. The industry will continue to grow as it adopts new technology and continuous efforts into research. The industries have gone from local to global value chains over the past few years. Research was conducted to develop a framework for supply chain resilience in renewable energy operations. This is to improve global supply chain by collaboration between designers, manufacturers, suppliers, original equipment manufacturers and logistics. The framework leaves room for integration of advanced technology such as internet of things, blockchain and artificial intelligence. The changing industries required a mix in energy sources, renewable is one which could provide balance on the global supply chains. The proposed framework is flexible for application in solar, wind and bioenergy to aid sustainability (Ekene Cynthia Onukwulu et al., 2023).

Paper manufacturing involves the primary and secondary industry, extraction of raw material, pulping, refining, forming and pressing. In this research an intelligent digital twin based on artificial intelligence for a paper manufacturing factory is proposed. A predictive model is included to do wear analysis on various components and equipment in the production line. The results show improved efficiency and reduced maintenance costs (Zhang et al., 2023). The future of maintenance in many industries lies in the ability to reduce wear and tear in critical equipment

of the organisation. It is predictive analytics that provides a tool in risk management and strategy improvement (Valli, 2024)

4. Data Collection

The bogie is a very important part of the train and through direct observation at the company's main depot we noticed many wheels flat spots. When the wheel locks or slips when braking, it can create flat marks, causing an uneven contact surface with the track. Flat spots can create excessive noise, vibration and potentially damage the track. This is because railway infrastructure in South Africa is damaged by vandalism and theft. Wheel thread damage can be caused by objects such as rocks or foreign objects on the rails, which can damage the wheel rails. Irregular or bumpy tread surfaces can affect wheel performance and increase wear. This is a signal-based analysis method for assessing the state of equipment and location of the fault. (Dai et al., 2021) further makes an example with the trackside acoustic system for detecting railway vehicle bearing faults. The equipment is placed along the railway line, as the train passes it picks up irregular noises from the bearings. The disadvantage is the equipment is fixed on the rail side not able to move with the vehicle. The diagnostic technology for gears mainly revolves around the condition monitoring of gears and bearings. The main fault modes of transmission machinery can be summarized into two categories, electrical and mechanical faults. If these two types can be effectively detected and identified, most transmission machinery fault diagnosis problems can be solved.

5. Results and Discussion

We are now in the age of Industry 4.0, where many industries have big data environments. Physics and smart grid analytics combine to realize new thinking on production management and factory transformation. In the future, we will see a shift from a conventional business model to a more service-oriented design. This is due to the large amount of data that companies have to manage on a daily basis. This information is fed back into the process through product service health monitoring. Total Productive Maintenance and Product Service System in bogies maintenance planning leads to more efficient and effective maintenance processes, customized maintenance services, improved asset reliability, availability and reduced costs for the rail company (Figure 3).

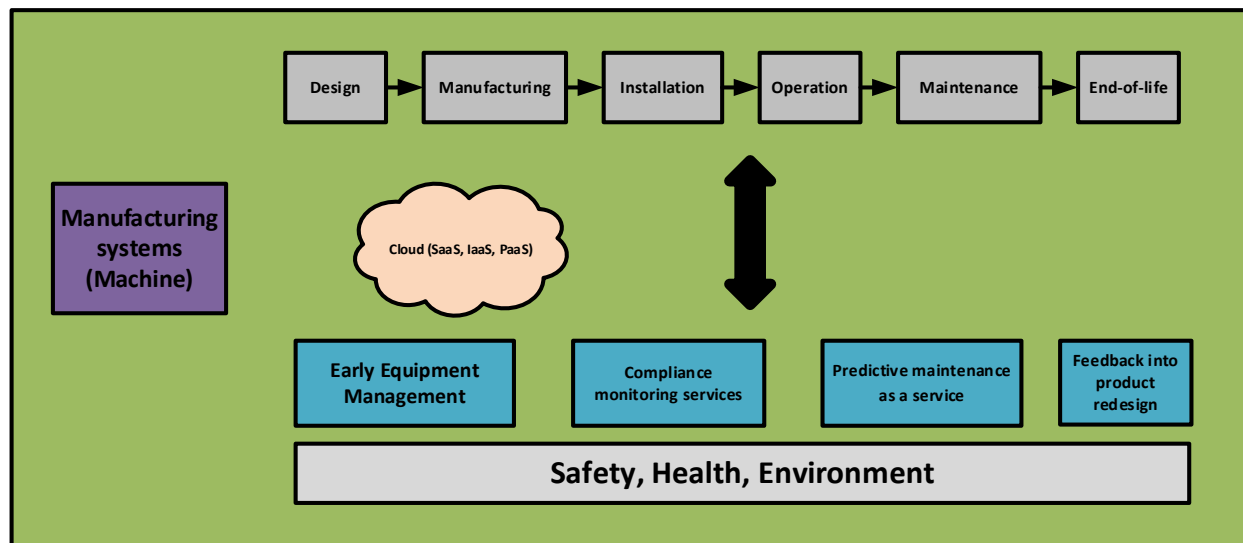


Figure 3. Total Productive Maintenance Integrated with Product-Service Systems into the manufacturing industry

The complexity of system design for products and services requires the search for alternatives through evaluation. Traditional manufacturing companies may have difficulty implementing PSS design, so evaluation is important to find the right method. The design of railcars is the responsibility of engineers. As customer demands increase, the integrated development of products and services must continually evolve to meet customer needs. The digital age is defined by networks via the Internet or cyber-physical systems. Product-service systems require an approach based on economic, social, and environmental goals. A) Integrate rail car systems through sensors and devices. B) service provision, and c) a business model that provides the right balance for manufacturers, customers, and suppliers. A very

clear indication of failed mechanical parts is abnormal increase in temperature, this could be used as an assessment key performance indicator for fault identification. Whether the bogie one, two or three axles by monitoring the axle temperature a conclusion can be about whether the component exceed the safety threshold.

We need to recognize TPM and PSS methodologies that are pertinent to the problems experienced in bogie operations. The evolution of product services has led to the development of various design methodologies over the years. A review of the literature shows that there are many products that provide additional services to the product that are not highly integrated. Physical assets in industrial plant are equipped with smart sensors, which connect them to the internet and create a networked physical system. The PSS-TPM model will be applied to research fields such as smart environments, healthcare and logistics. Beyond these applications, Product Service Systems provide a wide range of benefits to the manufacturing industry by enabling more efficient monitoring and control and optimization in a cost-effective manner.

6. Conclusion

The manufacturing sector is dominated by the industrial components needed to manufacture and assemble trains, such as heavy equipment, electrical equipment, computers and tools. Product-service systems in train bogie fleet and maintenance planning can lead to improvement and cost saving for the organization. Data analytics play a major role when an organization has to manage a large fleet of trains with big data to track component degradation and conditioned based maintenance. The proposed is inclusive of cloud computing methodologies namely infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). Depending on requirements, Total Productive Maintenance model work well with result-oriented Product Service System. Machine learning and artificial intelligence are among the key enabling technologies of Total Productive Maintenance 4.0. The application of AI on the manufacturing environment are not limited to the remote monitoring as we see several applications on machinery. Predictive technologies such as vibration monitoring, oil analysis, temperature sensing, acoustic emissions, and ultrasonic testing are also commonly used to measure machine health. The types of industrial sensors used for the machines include Position/Velocity sensor, Proximity sensor, Force/Pressure sensor and Vibration/Acceleration sensor. Monitoring component KPIs leads to early failure detection, which is crucial in the transition from a time-based preventive maintenance to a condition-based predictive maintenance (PdM) strategy. The integration of products and services allows you to formulate the right maintenance strategy. For bogies, this includes preventive, predictive and conditional maintenance depending on desired service level and maintenance needs. The product service system bundles the bogie physical subsystem with value-added services for maintenance, monitoring and diagnostics. This improves maintenance efficiency, reduces downtime, and optimizes resource allocation. Internet of Things technology can provide efficient connectivity solutions for a variety of use cases, both large-scale and critical IoT. Some of the most important requirements when considering large-scale deployments of these services include low deployment costs and long battery life. Low device cost, extended coverage area, support for many connected devices (extensibility), and security and privacy.

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Biographies

Trevor Shihundla is an African Male. Currently employed at University of South Africa as an Adjunct Academic. A well experienced Industrial Engineer with a 10-year history of Teaching, Research, Business Process Improvement and Operational research in Pharmaceutical, Automotive, Consulting, Rail and Academia. Trevor earned a Masters' degree in Industrial Engineering, where he was Gibela Research Chair Scholar and Currently pursuing a PhD in Industrial Engineering as CSIR scholar. His areas of expertise include new venture creation, railcar maintenance, operations management, production line balancing, leadership, automation, project management, simulation, lean principles, Product-Service engineering, problem solving skills and Game-Based Learning.

Dr. Matshidiso Moso is a dynamic academic, researcher, and mentor in the Department of Industrial Engineering at the Durban University of Technology (DUT). Her expertise lies in lean manufacturing, Total Productive Maintenance (TPM), and kaizen-based process enhancement, integrated within sustainability frameworks to promote environmentally responsible industrial systems. Her research advances sustainable production, digital transformation, and industrial optimization, with a particular focus on developing data-driven models that align with the UN Sustainable Development Goals (SDGs). Through innovative integration of TPM and Product-Service System (PSS) principles, Dr. Moso contributes to the modernization of engineering systems that support Industry 4.0 and climate-resilient manufacturing.

Prof. Tiaan Oosthuizen is a professor in Industrial Engineering focusing on strengthening sustainable supply chains and reducing ESG-related risks through strategic technology management, particularly the early identification, acquisition and protection of critical technologies across product, service and business lifecycles.