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Leveraging Smart Maintenance for Satellite Health Preservation

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Abstract

This paper presents a comprehensive literature review of smart maintenance techniques used in manufacturing, aviation, and electric automobiles, with the objective of identifying strategies to optimize the longevity and sustainability of satellite operations. This study assesses the latest advancements in smart maintenance, including data analytics, machine learning, artificial intelligence, and the integration of sensor technologies. These methods are suggested to reduce downtime, cut overall maintenance costs, and increase functional or component reliability and reusability. This study explores state-of-the-art maintenance approaches and industry best practices and examines their applicability in space. The research outlines the advantages of applying smart maintenance techniques to satellites, including enhanced operational efficiency, operational life-time extension, and overall cost-effectiveness. Moreover, the research proposes that the space industry can utilize the findings as a blueprint for customized satellite maintenance solutions and towards the establishment of standards and policies. This paper emphasizes the importance of adopting advanced maintenance procedures as a critical step towards a circular space economy that prioritizes sustainability and efficiency in space missions. This research contributes towards the sustainable future of the space industry by starting the dialogue on advanced smart maintenance technologies. It offers insights into improving satellite maintenance practices and encourages further research and collaboration to overcome implementation barriers. Furthermore, maintenance strategies are presented as a vital component towards space sustainability, enabling sustainable, reliable space missions, also aligning with the goals of a circular space economy.

Keywords: Space Sustainability, Predictive Maintenance, Smart Maintenance, Satellite Health, Circular Economy

1. Introduction

The number of human-made objects in Earth's orbit continues to grow each year, further accelerated by the launch of mega-constellations such as Starlink [1, 2]. To mitigate risks associated with orbital overpopulation and the creation of space debris, regulatory bodies suggest lowering the current recommended post-mission lifetime of 25 years, with organizations like the FCC recommending 5 years [3]. This end-of-life approach prevents materials being reused and negatively impacts Earth's atmosphere through the release of chemicals and the creation of metal particles during atmospheric burnup [4]. Instead of focusing solely on a decommission of satellites as a solution to orbital overpopulation, using Smart Maintenance and Health Monitoring techniques to extend the Remaining Useful Life (RUL) of satellites and investigating if they can be repurposed for continued use during their post-mission lifetime can offer a sustainable alternative for preserving the orbital environment. By implementing smart health monitoring, operators can minimize the number of redundant satellites in constellations, as faults can be detected and addressed in real-time. This decreases the overall need for new satellites, conserving resources, lowering costs, and minimizing the environmental impact of frequent launches and satellite disposals. This proactive approach can support the application of circular economy-based strategies in space, where extending the lifecycle of satellites can reduce waste and also enhances overall operational sustainability [5]. Satellite technology has advanced significantly in recent years and satellites are becoming more flexible in their abilities. Some satellites are already equipped with sensing equipment for health status reporting, reducing the barriers to implementing smart maintenance solutions [6, 7]. Capitalizing on existing capabilities and combining them with other Industry 4.0 technologies such as Machine Learning and the Internet of Things (IoT) [2] can enable satellite networks to act as self-monitoring sensor networks, providing the data necessary for smart maintenance activities in orbit [6]. This process can allow for regular re-calculation of a spacecraft's RUL, and more dynamic planning of spacecraft repurposing to extend its operational life and improve the sustainability of its operations. To investigate how emerging technologies can enable longer operational lifetimes of satellites and enhance sustainability in space, this review examines literature on maintenance strategies employed in several key systems, including stabilizing systems, propulsion mechanisms, power subsystems, communication networks, thermal control systems, structural components, and optical instruments. The focus of this review is on preventive, corrective, and predictive maintenance methods, which are essential for the optimal functioning of these systems and maximizing both their design life and remaining useful life. In particular, this paper examines literature on maintenance techniques in comparable industries and investigates industrial smart maintenance and health monitoring approaches. Furthermore, this paper presents a case study on using satellite data to implement these smart maintenance and health monitoring solutions.

2. The Role of Maintenance in the Space Industry

Maintenance activities, which can be classified as preventative, corrective, or predictive, play a key role in implementing a circular economy [8]. Preventative maintenance aims to extend the RUL of an asset by preserving or improving its condition before a fault occurs, reducing the risk of future faults that could cause downtime or loss of the asset [9]. By maximizing the RUL of an asset, preventative maintenance activities reduce the need for additional resources to be used in the constant manufacture of new assets, making the production and lifetime of that asset more sustainable [9]. Predictive maintenance is a subset of preventative maintenance which enables operators to forecast the maintenance needs of their assets using techniques like statistical analysis or machine learning [10]. This is discussed in further detail in Section 6.1. Corrective maintenance seeks to repair or restore an asset after a fault has developed. Corrective maintenance is often more disruptive, costly, and complex than preventative maintenance. It also may not extend the RUL beyond the original estimate, instead enabling the asset to continue useful production until its original end date, adding minimal benefit in terms of sustainability [10]. Industries such as aviation have long incorporated maintenance activities into their lifecycle design to meet necessary safety requirements [11]. Effective maintenance strategies not only enhance sustainability but also increase the financial Return on Investment (ROI) by enhancing the asset's productive capacity. This further incentivizes an optimization of maintenance schedules and to prioritize preventative maintenance during the operational lifetime of a satellite [12, 13].

2.1 Factors Affecting Satellite Operability

Satellites are complex systems composed of multiple subsystems and components. Key subsystems include Attitude and Orbit Control Systems (AOCS), power supply systems, and communication interfaces with ground stations. The space environment, characterized by extreme temperature variations and exposure to ionizing radiation, poses significant challenges to these components. Over a satellite's mission lifetime, these environmental factors lead to varying levels of degradation in each component [14]. The most significant factors affecting satellite operability include radiation exposure, thermal cycling, and micrometeoroid impacts. Each of these stressors progressively degrades satellite components, impacting their functionality and reducing their operational lifespan. [15, 16]

2.2 Satellite Component Degradation

A comprehensive study conducted by Tafazoli [17] analyzed 156 spacecraft failures and highlighted the importance and vulnerability of the AOCS and power subsystem. 59% of all failures in this study were caused by degradation of these subsystems. Within the AOCS, gyroscopes, momentum wheels and thrusters were particularly prone to failure, accounting for 17% and 14% of AOCS-related issues, respectively. Most failures within the AOCS were mechanical in nature, including lubrication losses and metal abrasion of momentum wheels. Other studies corroborate these findings, indicating that mechanical failures are more prevalent than other types of failure within the AOCS [18]. In addition to wear-out failures, the AOCS also experiences a high rate of failure within the first year of orbital operation, which can be attributed to design flaws and manufacturing defects [17, 18]. This highlights the crucial importance of robust design and manufacturing processes in the development of spacecraft hardware. Furthermore, literature suggests that the AOCS may become the limiting factor as satellite operators seek to increase and maximize mission lifetimes [18], aligning with circular economy principles focused on slowing the product lifecycle. In the power subsystem, the solar array and battery were the most failure-prone components, with the solar array being the leading cause of functional failures across all missions and contributing to 49% of power subsystem failures. The solar array, often the most exposed component on a satellite, is subject to constant wear and degradation, directly impacting the satellite's power generation capacity, leading to cascading effects on other subsystems. These findings are further corroborated by other studies on specific spacecraft failures [18-21] which consistently emphasize the criticality of the AOCS and power subsystem in maintaining satellite functionality. Unlike other subsystems, which often incorporate redundancy measures or backups, the power subsystem and AOCS present unique challenges. Solar arrays typically lack physical backups, and alternative power sources are usually unavailable [17]. Implementing redundancy in the AOCS is also challenging. Launching a satellite with a back-up momentum wheel would be costly, not only with the additional part manufacture but of increased launch costs due to the extra mass. Moreover, implementing low-level redundancy for components like bearings or lubricant is impractical [18]. Therefore, minimizing degradation of these subsystems before launch is essential for maximizing the satellite's operational lifetime. Whilst some data on spacecraft failures is available for analysis, the details regarding failure causes are often incomplete, and the data may not be regularly updated or maintained. This limitation complicates the prediction of degradation based on historical data and underscores the importance of optimizing component design and manufacturing processes to protect against the most critical failure risks identified [22].

3. Maintenance Activities in Other Industries

Industries such as aviation, robotics, and energy production make use of similar components as used in satellites, such as stabilizing systems, solar panels, and optical instruments. These sectors are already employing preventative and predictive maintenance techniques to maximize their RUL and optimize their design life.

3.1 Stabilizing Systems in Aviation and Robotics

Stabilizing systems, such as gyroscopes and momentum wheels, are critical components in aviation and robotics applications. These systems require precise maintenance to function correctly. Preventative maintenance, including regular lubrication checks, is vital to prevent wear and tear. Lubrication loss and metal abrasion are common issues that can significantly impair performance [23]. Software-based predictive maintenance techniques, such as vibration analysis and performance monitoring, are used to detect early signs of mechanical failure, allowing for timely intervention [24]. Additionally, regular calibration of gyroscopic instruments ensures accuracy, which is critical in aerospace engineering and robotic applications [25].

3.2 Power Subsystems: Solar Panels and Industrial Batteries

Solar panels and industrial batteries are integral to power subsystems in renewable energy applications and industrial power supplies. Solar panels are subject to environmental factors that can lead to efficiency loss over time. Regular cleaning and inspection are essential to remove dust, debris, and other contaminants that may reduce power output [26]. Monitoring systems are often employed to track the performance of solar panels and detect any deviations from expected output, which can signal the need for maintenance [26]. Industrial batteries, particularly those used in uninterruptible power supplies (UPS) and electric vehicles, require rigorous maintenance to ensure they operate effectively. Capacity testing is a common practice to assess the battery's ability to store and deliver power under various conditions [27]. Additionally, thermal management systems are crucial in preventing overheating during charging and discharging cycles, which can lead to premature failure [28]. Regular replacement schedules based on usage and environmental conditions are also implemented to maintain reliability [27].

3.3 Communication Networks: Telecommunication Systems and Data Networks

Communication networks, including telecommunication systems and data networks, are critical for the seamless transmission of data and signals. These systems are vulnerable to signal degradation due to several factors such as noise, attenuation, and thermal stress [29]. Regular signal integrity tests are conducted to detect and rectify these issues, ensuring that communication remains reliable and efficient [30]. Furthermore, hardware upgrades are periodically performed to replace outdated components and enhance system capabilities, which is a widespread practice in data centers [31].

3.4 Thermal Control Systems: HVAC Systems in Industrial Buildings and Data Centers

Thermal control systems are vital in maintaining optimal operating temperatures for various industrial applications. In industrial buildings and data centers, HVAC (Heating, Ventilation, and Air Conditioning) systems are essential for regulating temperature and ensuring the smooth operation of critical systems [32]. Regular coolant checks and replacement, as well as insulation maintenance, are common practices to prevent overheating or overcooling, which can lead to equipment failure. System diagnostics are also routinely conducted to monitor performance and make necessary adjustments to maintain efficiency [33].

3.5 Optical Instruments: Maintenance in Scientific Instruments and Cameras

Optical instruments, such as lenses and sensors, are critical components in various scientific and industrial applications. These instruments require meticulous maintenance to ensure optimal performance. Regular cleaning and polishing of optical surfaces are essential to maintain clarity and prevent signal distortion [34]. Additionally, protective coatings are often applied to minimize the effects of environmental exposure, such as radiation or physical impacts, which can degrade the optical quality over time [27]. Periodic alignment checks are also necessary to ensure that optical components remain correctly positioned, which is crucial for maintaining accuracy in scientific measurements and imaging applications [35].

4. The Circular Economy in Space

The space industry can greatly benefit from smart maintenance and strategies that are rooted in circular economy principles. The high cost of satellites, depletion of virgin materials and resources, and the environmental impact of space operations make it essential to investigate satellite lifecycle extensions, optimizing resource use, and to minimize overall waste. To gradually transition into a Circular Economy (CE) can represent a significant shift in both industrial operations and product design, moving away from the traditional linear approach of “take, make, dispose” a satellite, to a sustainable approach that prioritizes keeping satellites and the materials longer in operation. Foundational strategies like reusing, remanufacturing, or recycling satellites can be utilized to achieve these goals, along with applying more nuanced approaches to extend a satellites operational lifetime [36]. This transformation in the design and manufacturing of satellites is also driven by increasing environmental concerns and resource scarcity, and a growing economic motivation for reducing material costs and decreasing waste generation [8]. A main point of the digital transformation in manufacturing is to focus on product life cycle management. This focus encourages businesses to design products that are more durable, repairable, and upgradable [8]. This shifts the focus from merely improving end-of-life recycling processes to ensuring that products have a longer, more productive operational time and that components of the products can also be reused in new products. By integrating modularity and standardization into design, manufacturers can facilitate easier repairs and upgrades, thereby fostering innovation in sustainable product development [36]. Product design under a CE framework also aligns closely with the concept of “servitisation”, where companies move away from selling physical products to providing services based on the functionality those products offer [37]. This transformation from product ownership to product-as-a-service (PaaS) not only promotes the use of durable, high-quality products but also offers businesses an ongoing revenue stream by maintaining and servicing the products they lease to customers [38]. As such, businesses are incentivized to ensure their products last longer and perform better over time, increasing the need for optimized and predictive maintenance capabilities. Moreover, the CE transformation is inextricably linked to the rise of new business models. Companies adopting CE principles are shifting towards models that are based on value retention, including leasing, sharing, and take-back schemes, where products or their components can be reintroduced into the production cycle after use [39]. These business models not only reduce the environmental impact by lowering material input and waste, but also create new opportunities for customer engagement and brand loyalty through enhanced service offerings [36]. In this way, CE is transforming the fundamental logic of business operations, encouraging firms to explore innovative ways of creating value while mitigating their environmental footprint [8]. In contrast to traditional recycling approaches, which tend to focus on managing waste after products have reached the end of their life, the CE framework promotes a more comprehensive approach to sustainability that prioritizes proactive strategies for extending product life. This shift towards life extension can include practices such as preventive maintenance, product refurbishment, and remanufacturing, all of which contribute to reduced resource consumption and a slower turnover of goods [8]. Consequently, the CE is not merely about improving waste management, but about fundamentally rethinking how products are designed, used, and eventually reintegrated into the economy. The CE transformation is more than just a set of strategies; it represents a new economic model that integrates sustainability into the core of manufacturing, product design, and business practices. By extending product life, promoting servitisation, and adopting innovative business models, CE offers a pathway for industries to achieve long-term economic and environmental resilience [8, 36]. Investigating how to apply circular economy principles and the aforementioned strategies to satellites can benefit the space industry by promoting extended lifespans of satellites, reduced overall mission cost, and a decreased environmental impact on Earth and in space.

4.1 Integrating Circular Economy Techniques into Satellite Operations: A Business Model Perspective

As the space industry evolves, integrating circular economy principles becomes essential for sustainable growth. This section discusses how the repurposing, reusing, and previously detailed business models can be effectively applied to satellite operations, creating sustainable and economically viable solutions.

4.1.1 Repurposing Satellites in Operation

The repurposing of satellites involves extending their RUL by assigning them new missions once their original functions can no longer be performed effectively. Business models that support this technique include Lifecycle Extension Services, where companies can offer services that assess and reconfigure satellites to take on new roles, extending their operational life and deferring the environmental cost of deorbiting and launching new satellites; and Flexible Use Licensing, where satellite operators can offer flexible licensing models that allow users to switch satellite roles, facilitating a dynamic use of space assets based on demand and satellite capability.

4.1.2 Reusing Satellite Components

Reusing components from decommissioned satellites or those nearing the end of their operational life is another approach. This involves designing satellites so that certain components, such as sensors or propulsion units, can be easily transferred to other satellites or platforms. Business models here include Component Leasing, where companies specialize in leasing satellite components, which can be swapped in and out of different satellites as needed, like the automotive industry's parts leasing; and encouraging the design of modular satellites where components are standardized and interchangeable across different systems. This would promote a "plug-and-play" approach to satellite construction and maintenance.

4.1.3 Circular Supply Chains

Building circular supply chains in the satellite industry involves establishing systems that facilitate the return, refurbishment, and reuse of satellite components. Business models that promote circular supply chains include Reverse Logistics Services, where companies that specialize in the recovery and refurbishment of satellite components from space, which are then either reused or recycled; and Sustainability Certifications that are offered to satellite operators that adhere to circular economy principles, enhancing brand reputation and consumer trust. To support these operations, sustainable business practices must be integrated into every level of organizational strategy. Businesses could implement subscription-based models, where satellite services are offered under a service agreement that includes maintenance, upgrades, and eventual repurposing or recycling. Another option is investigating partnerships and collaborations between governments, commercial enterprises, and NGOs to share knowledge, resources, and technologies that facilitate the circular use of satellites. Implementing circular economy principles in satellite operations requires innovative business models that promote sustainability and resource efficiency.

4.1.4 Satellite-as-a-Service (SaaS)

The Satellite-as-a-Service model transforms satellite operations from a product-based to a service-based approach. Operators lease satellite capabilities rather than owning the satellites outright. This model encourages manufacturers to design satellites that are more durable and easier to maintain, as the responsibility for the satellite's performance and longevity remains with the service provider. This service-based approach aligns with the service-dominant logic in marketing, which views the value of a product as the service it provides rather than the physical good itself. Vargo and Lusch [40] discuss this in their work on service-dominant logic, highlighting how it fosters longer product life cycles and sustainability.

4.2 Challenges and Opportunities in Transitioning to Circular Economy Practices in Satellite Operations

4.2.1 Challenges

The adaptation of circular economy principles to the satellite industry faces significant technological challenges, particularly in designing satellites that are modular and capable of being repurposed or having components reused. Overcoming these barriers requires advances in material science and engineering to develop components that can withstand multiple missions and harsh space environments [41]. Transitioning to a circular economy model also requires substantial upfront investment in research and development, as well as in the restructuring of existing production lines to accommodate new designs and processes. There is also the challenge of proving the economic viability of these new models to stakeholders and investors [42]. Finally, the lack of specific regulations that support the circular economy in space activities can hinder the adoption of these practices. Effective policy frameworks are essential to facilitate recycling, repurposing, and the safe deorbiting of satellites [43].

4.2.2 Opportunities

By implementing circular economy practices, the satellite industry can significantly reduce its environmental impact, decreasing both space debris and the carbon footprint associated with manufacturing and launching new satellites [44]. Circular economy models can lead to substantial economic benefits through cost savings in materials and waste management, as well as by creating new revenue streams from services such as on-orbit servicing and component leasing [43]. The shift towards circular economy practices can spur innovation in satellite design and operations, leading to innovative technologies and methods that offer competitive advantages in the global market. This can also foster collaborations across industries, expanding the technological frontier [45]. Satellite components and production systems share several commonalities in their design and operational needs. Both rely on the integration of complex systems that require meticulous maintenance, continuous monitoring, and efficiency optimization. Understanding these similarities is crucial for exploring how circular economy techniques developed on Earth can be adapted for use in space-based systems.

5. Software-Based Maintenance

Degradation of computational power, machine overload, and process bottlenecks in production lines are common challenges that can reduce overall system efficiency, increase downtime, and lead to significant financial and resource waste. Fortunately, several software-based solutions can mitigate these issues, leveraging optimization, resource-sharing strategies, and outsourcing of critical processes. Software-based solutions such as optimization algorithms, resource sharing, and outsourcing offer effective ways to address the challenges of computational power degradation, machine overload, and process bottlenecks in production systems. By leveraging load balancing, machine learning for predictive optimization, cloud-based computation, and distributed manufacturing, companies can optimize their workflows, maintain efficiency, and support circular economy goals. These solutions allow for flexible, scalable, and sustainable approaches to managing production and computational systems under stress. Below is an analysis of potential solutions.

5.1 Optimization Techniques

Optimization algorithms can be implemented to improve the overall efficiency of machines and computational systems. These algorithms ensure that resources are allocated effectively, and that systems are not unnecessarily overburdened.

5.1.1 Load Balancing Algorithms

Load balancing involves distributing tasks across multiple machines or computational resources to prevent overload on any single entity. In computational systems, load balancing can distribute processing tasks across servers or processors, ensuring no single CPU becomes a bottleneck. This strategy is particularly effective in cloud computing environments, where tasks are shared across multiple servers [46]. In production systems, load balancing can be used to distribute manufacturing tasks across machines on the production line. For example, automated manufacturing plants often use optimization algorithms to distribute workloads evenly across robots or machines to prevent any one station from becoming overloaded [46].

5.1.2 Machine Learning for Predictive Optimization

Machine learning (ML) models can optimize resource use by predicting when machines are likely to become overloaded or when computational power will degrade. Predictive algorithms analyze historical performance data and real-time inputs to adjust resource allocation dynamically. For example, ML algorithms can predict when a machine is likely to overheat or require maintenance and shift workloads to other machines preemptively [47]. In cloud computing, predictive ML can be used to allocate more processing power to tasks expected to demand more resources, preventing computational degradation [48].

5.1.3 Process Optimization

In production systems, software can optimize entire processes by identifying bottlenecks and redistributing tasks accordingly. Software solutions such as enterprise resource planning (ERP) systems can track production flow and identify stations where work piles up due to inefficiencies. For example, in a factory where one station slows down due to mechanical issues, software can reallocate tasks to other stations or adjust schedules to prevent delays [49].

5.2 Resource Sharing and Virtualization

Resource sharing is another key solution to address machine overload and computational degradation. By enabling multiple machines or systems to share resources, companies can reduce the strain on individual components and optimize the use of available capacity.

5.2.1 Cloud Computing and Virtualization

Virtualization technologies, particularly in cloud computing environments, enable companies to share computational resources efficiently. Virtualization allows physical resources to be divided into virtual machines (VMs) that can be dynamically allocated based on demand [50]. This means that when computational power begins to degrade or reach its limit, additional resources from other VMs or cloud infrastructure can be allocated to maintain performance levels. In production systems, resource-sharing solutions can involve sharing computing power between machines. For example, if one machine's onboard computing system is overloaded, nearby machines on the production line can take on some of the computational tasks. This distributed computing approach can prevent bottlenecks and ensure continued production flow.

5.2.2 Shared Machine Usage in Manufacturing

Resource sharing is not limited to computational systems. In manufacturing, machine-sharing strategies allow multiple processes or tasks to be allocated to different machines when the primary machine is overloaded. For example, if one CNC machine becomes overloaded with tasks, software can allocate part of the work to another machine that has available capacity, optimizing overall workflow [30].

5.3 Outsourcing Critical Processes

When internal systems are no longer capable of handling certain workloads or processes due to computational degradation or production overload, outsourcing can be an effective solution. Outsourcing critical or resource-intensive processes to external partners allows companies to maintain efficiency without investing in additional internal capacity.

5.3.1 Cloud-Based Computation Outsourcing

In computational systems, outsourcing critical processes to cloud providers is a common solution when internal systems reach their limits. Cloud services like Amazon Web Services (AWS) and Microsoft Azure offer scalable computing resources that can be tapped into as needed [51]. For example, in the event of an overload in internal servers, companies can offload computational tasks to the cloud, ensuring continuity without requiring immediate hardware upgrades [52].

5.3.2 Outsourcing Manufacturing Processes

In production systems, outsourcing certain high-demand tasks to external manufacturers or subcontractors can help reduce overload. For example, companies facing capacity constraints might outsource part of their production line to specialized manufacturers during periods of peak demand. This approach ensures that production continues smoothly while avoiding the cost of investing in new machines [53]. For example, automotive manufacturers often outsource the production of specific components like electrical systems or transmission units during high-demand periods.

5.4 Cloud-Based Manufacturing (CBM) and Distributed Manufacturing

An emerging solution to computational and production overload is the adoption of Cloud-Based Manufacturing (CBM), which integrates cloud computing into manufacturing processes. CBM allows manufacturers to share resources such as design data, production capacity, and even machine availability across a network, reducing the likelihood of bottlenecks or overload in any single system [50].

5.4.1 CBM for Production Line Flexibility

In CBM, machines across separate locations can be interconnected through the cloud to share workloads dynamically. If a particular machine or station in a factory experiences an overload or bottleneck, CBM software can allocate that task to a machine in a different location with available capacity [30]. This allows companies to dynamically optimize production lines and avoid inefficiencies caused by local constraints.

5.4.2 CBM in Distributed Manufacturing

Distributed manufacturing, enabled by CBM, allows manufacturers to decentralize production by outsourcing specific components of the manufacturing process to various locations. This strategy increases flexibility and reduces the strain on any one production line [54]. For instance, rather than concentrating all production tasks in a single factory, companies can leverage a network of smaller, geographically dispersed factories to handle specific tasks when one factory reaches its capacity.

6. Smart Maintenance and Health Monitoring

Smart maintenance and health monitoring plays a critical role in supporting circular production systems, lowering downtime, extending asset life, optimizing resource use, and minimizing waste. By leveraging predictive analytics, machine learning, and adaptive algorithms, smart maintenance and health monitoring enhances production efficiency and aligns with circular economy principles by reducing the need for premature replacements and resource-intensive interventions. Table 1 summarizes how industrial smart maintenance practices relate to sustainable circular economy principles, and how these practices may translate into use in satellite networks vis software-based, smart interventions.

6.1 Predictive Maintenance

Predictive maintenance relies on real-time data and sensor technology to monitor machinery and predict potential failures before they happen. This approach reduces downtime, prevents sudden breakdowns, and allows for timely maintenance, extending the life of machinery and reducing waste [47]. For example, in automated manufacturing lines, predictive maintenance helps prevent failures that could disrupt production, leading to more sustainable operations and resource conservation [48]. In the automotive industry, manufacturers like BMW and Tesla use predictive maintenance to keep their production lines running efficiently by identifying equipment needing repair before failure occurs, avoiding unnecessary energy consumption and material waste [54].

6.2 Load Balancing and Optimization

Smart maintenance systems optimize resource usage by employing load balancing techniques. These systems distribute tasks evenly across machinery, preventing the overuse of specific assets and ensuring smoother operation, reducing the wear on individual machines [46]. This load optimization not only enhances productivity but also prolongs machinery life, contributing to a circular approach by avoiding the need for frequent replacements. For example, in semiconductor manufacturing, load-balancing algorithms optimize machine utilization to maintain consistent production rates, reducing both downtime and energy consumption [30].

6.3 Repurposing and Asset Management

Smart maintenance enables the repurposing of degraded machinery for less demanding tasks, thus extending the lifecycle of assets. Machines that may no longer be suitable for high-precision tasks can be reallocated to perform simpler functions, such as packaging or inspection, thus preventing premature disposal [53]. This approach fits into circular economy strategies by maximizing the use of available resources and minimizing waste. For example, older industrial robots may be repurposed to perform non-critical tasks once their precision capabilities decline. This prevents early retirement of expensive equipment and reduces the environmental impact of manufacturing new machines [46].

6.4 Outsourcing High-Demand Processes

When internal systems are strained during high-demand periods, outsourcing can help reduce the load on production assets, extending their operational life. Outsourcing specific, resource-intensive processes to external suppliers allows internal resources to be focused on core production tasks, reducing wear and preventing overloading [53]. For instance, electronics manufacturers often outsource the production of complex components such as circuit boards to specialized suppliers during peak production periods, relieving their in-house systems from potential overload and reducing downtime [51].

7. Smart Maintenance for Satellites: A Case Study

Some aspects of satellite deterioration are age-related and well understood through analysis of historical data and statistical modelling. However, this modelling is only possible when sufficient data is available. Satellite constellations are typically built in smaller groups that are launched in waves and consist of different hardware and software specifications, making traditional statistical modelling less effective at making deterioration predictions [54]. Additionally, many potential faults are related to environmental factors rather than its age exclusively. The probability of these factors resulting in faults often does not strongly correlate with how long the asset's time is in service, making the scheduling and execution of preventative maintenance challenging [8]. These failure modes correlate with other measurable variables, such as radiation exposure or physical damage caused by space

Table 1. Summary of how industrial smart maintenance practices relate to the circular economy and satellite network

Industrial Smart Maintenance Practices	Description	Circular Economy Principle	Application on Satellites
Predictive Maintenance	Uses real-time data and AI to predict machinery failures and perform proactive maintenance	**Rethink**, **Reduce**	Use AI-driven predictive maintenance to monitor critical components like batteries and solar panels, adjusting operational parameters to avoid failures and extend life.
Load Balancing and Resource Optimization	Distributes workloads across machines to prevent overloading and optimize resource use	**Reduce**, **Rethink**	Share computational resources between satellites in a constellation, dynamically shifting tasks to satellites with available capacity, optimizing energy and processing power.
Adaptive Control Systems	Machine learning systems that adjust machine operation (e.g., speed, load) based on real-time conditions	**Rethink**, **Reduce**	Implement adaptive control over mechanical parts (e.g., antennae, propulsion systems) to reduce wear and tear, extending satellite life by adjusting usage based on conditions.
Repurposing Degraded Assets	Older machines are repurposed for less critical, non-core functions	**Reuse**, **Repurpose**	Repurpose satellites for lower-demand applications, such as educational purposes, scientific experiments, or less critical communication tasks after their primary mission is complete.
Outsourcing High-Demand Processes	Offload resource-intensive tasks to external or third-party systems during peak demand	**Reuse**, **Reduce**	Offload computational tasks or communication processing to ground stations or nearby satellites when satellite resources are nearing limits, reducing energy consumption.
Dynamic Energy Management	Optimizes the energy consumption of machines by adjusting power use based on real-time needs	**Reduce**, **Rethink**	Use AI for dynamic energy management of solar panels and batteries, optimizing energy use based on real-time conditions like sunlight availability and power demand.
Component Life Extension through Calibration	Extends the life of components by frequently recalibrating them for optimal performance	**Extend**, **Reduce**	Recalibrate sensors, gyroscopes, and other sensitive equipment to ensure they remain accurate and function optimally, preventing premature failure and extending operational life.
Virtualization and Cloud-Based Solutions	Shares computational tasks and resources via virtualized platforms and cloud computing	**Reduce**, **Reuse**	Virtualize satellite computing power to share resources with other satellites in the network, preventing overload and ensuring resource-efficient task distribution.
AI-Based Maintenance Optimization	Uses AI to continuously learn from performance data to optimize maintenance schedules and machine operation	**Rethink**, **Extend**	Implement AI to continuously optimize satellite operations, adjust maintenance schedules, and predict energy or component failures, thus extending operational lifetimes.
Repurposing Components for New Missions	When machines degrade, components can be reused for new tasks or systems	**Reuse**, **Repurpose**	Repurpose specific satellite components, like communication systems or sensors, for low-energy, lower-demand missions or even pass them on to newer satellites for extended utility.

debris, which can be used to predict an asset's future maintenance needs using predictive maintenance [56, 57]. If data on these variables can be collected in a timely manner, for example by using smart technologies such as digital sensors, it can be used as the basis for predictions needed for planning preventative maintenance. Instead of relying exclusively on statistical analysis for predictions, this data can be used as training data for ML models, which significantly improves the accuracy of these predictions. ML models can learn from large datasets and evolve over the asset's operational life, continually optimizing its maintenance schedule [12]. This reduces the risk of failure from under-maintenance and the risk of excessive spending from over-maintenance [13], in addition to making the production and use of the asset more sustainable. This combination of using smart devices and ML for predictive maintenance is known as Smart Maintenance [12, 58]. Smart Maintenance makes use of ML models to predict the RUL for an asset, without the need for frequent human-led inspections, which can be costly and challenging [59]. The aviation and manufacturing sectors have recently begun to implement Smart Maintenance techniques to enhance the efficiency of its predictive maintenance activities and improve the sustainability of their product lifecycles [12, 13].

7.1 Distributed Machine Learning

Once trained on data from ground-based test campaigns, ML models consume real data to establish patterns that can be used for predictive maintenance. This data, gathered from on-board sensors, is likely to contain proprietary and sensitive information about equipment performance and configurations. Secure data handling will be necessary to protect any private data consumed by the model as it continues to evolve and improve after being evaluated against validation datasets [6, 7, 60]. To improve data security and access to services such as smart contracts and device autonomy, integrating Distributed Ledger Technologies (DLTs), such as blockchain, into pre-existing smart ecosystems is being explored [61, 62]. DLTs offer robust and secure data storage, where encrypted copies of data are distributed across multiple devices. This decentralized approach mitigates the risk of data loss from a single point of failure in the system and reduces the likelihood of data interception or manipulation [7, 60, 63]. Using data parallelism, ML models can be trained on distributed datasets stored in Distributed Ledgers (DLs). Data is partitioned into smaller subsets to optimize storage across resource-constrained devices at the network's edge, such as satellites. Following a Decentralized Federated Learning approach, each device trains the ML model on its local dataset, communicating and synchronizing model updates with other devices upon completion [64]. Since user-based validation opportunities are limited in the orbital environment, once a local model update has been validated and added to the ledger, smart contracts can be used for adaptive learning to improve the accuracy of the shared ML model. This automates decisions around learning rate adjustments, triggering additional training rounds and execution of a validation dataset to assess the model's effectiveness against a predefined set of metrics [65, 66]. Whilst distributed ML at the edge allows the collected data to remain secure with its owner, that data has limited value to its owner as a standalone asset. By using a distributed ledger-based system, operators can monetize that data via payment of royalties, providing a financial incentive for both data collection and usage, in addition to the incentive of having a more reliable satellite. Smart contracts can facilitate this exchange of micropayments for use of data for model training, as well as enabling adaptive learning [63, 64]. An example of this architecture is shown in Fig. 1.

7.2 Key Challenges

Not all satellites are equipped with sufficient health monitoring equipment, making data collection for smart maintenance difficult. Addressing this issue requires the installation of additional hardware, such as processing chips or sensors, to facilitate effective data collection. This hardware could be integrated as an additional, modular sub-system on the spacecraft [7]. In addition, satellites typically have limited resources, such as processing power, memory, and energy, which constrains their ability to deploy computationally expensive and large ML models at the edge. Ongoing research into model compression technologies aims to mitigate this issue by reducing the size of deployed ML model, and advancements in edge computing are exploring how to optimize ML inference on resource-constrained devices [64, 67].

8. The Future of Smart Maintenance in Satellites: Potentials and Business Models for a Circular Economy in Space

The future of smart maintenance in satellites and leveraging circular economy principles in satellite technology offers promising potential, particularly through extending operational lifetimes, resource optimization and innovative circular business models. Just as industrial sectors have integrated practices such as predictive maintenance, load balancing, and adaptive systems to extend the life of assets and minimize waste, the satellite industry is beginning to explore similar pathways. Satellites, much like machines in industrial environments, face degradation over time. By implementing AI-driven smart maintenance, satellite operators can anticipate component failures -such as battery degradation or solar panel wear - and make proactive adjustments to extend their operational life. This practice aligns with the "Rethink" and "Reduce" circular economy principles, ensuring that satellites remain functional for longer periods, reducing the frequency of new launches and conserving resources. Business models based on service contracts for maintaining satellite constellations could emerge, where companies ensure operational longevity in exchange for continuous revenue streams. Resource-sharing models, such as load balancing, have become essential in cloud computing and manufacturing, preventing system overload, and optimizing energy use. In satellite constellations, a similar practice could allow satellites to share computational tasks or communication loads with neighboring satellites. This "Reduce" and "Reuse" strategy would ensure that satellites operate more efficiently, particularly during peak demand. Emerging cloud-based satellite platforms could monetize the sharing of computational resources between satellites, offering flexible pricing for bandwidth and processing power across constellations.

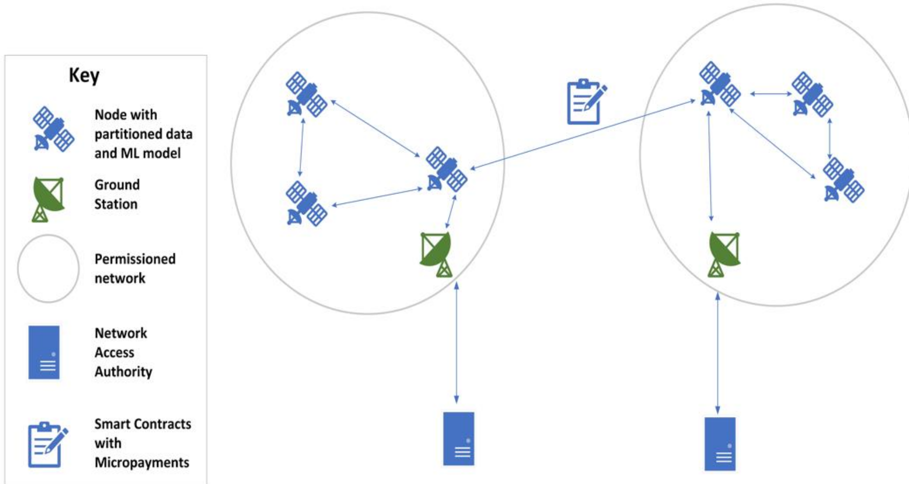

Figure 1. Architecture for distributed machine learning in a satellite network. Own graphic.

Just as industrial machines are repurposed for less demanding tasks as they age, satellites could be repurposed for lower-demand applications once their primary mission ends. A satellite designed for high-demand communication could, for instance, be reassigned to environmental monitoring or educational purposes. This practice taps into "Reuse" and "Repurpose" principles, ensuring that valuable hardware is not wasted and extends its functional life. Business models around "satellite leasing" could emerge, where older satellites are rented out for secondary purposes, creating a revenue stream from assets that would otherwise be decommissioned. Efficient energy use is critical in satellite operations, especially as solar panels and batteries degrade over time. AI-driven dynamic energy management could optimize how satellites harness solar energy, adjusting operations based on real-time conditions to ensure maximum longevity. This aligns with "Reduce" principles, making satellites more energy-efficient and sustainable. Satellite operators can adopt pay-per-use models, where users are charged based on the satellite's optimized energy consumption, promoting sustainability and long-term use of space assets. The satellite industry has promising potential for adopting circular business models that focus on extending asset life and optimizing resource use. These new models can include following examples:

Satellite-as-a-Service (SaaS): Offering satellites or satellite functions as a service rather than selling them outright. This model incentivizes operators to ensure the longest possible operational life for satellites, aligning with circular principles.

Satellite Refurbishment and Upcycling: Similar to refurbishing industrial machines, satellite operators could refurbish or upgrade older satellites for new missions, reducing the need for new materials and launches. Companies could monetize the refurbishment process by selling upcycled satellites for lower-cost missions.

Shared Satellite Networks: Creating shared satellite networks where multiple stakeholders can access a single satellite's resources (computational power, communication bandwidth) under a subscription model. This would maximize the utility of each satellite and prevent resource overuse.

On-Orbit Servicing, Assembly, and Manufacturing (OSAM): OSAM models extend satellite lifespans by performing maintenance, repairs, or upgrades directly in orbit. This model reduces the need to launch new satellites and directly supports sustainability by prolonging the service life of existing assets. The theoretical foundation for OSAM includes resource-based theory, which emphasizes the competitive advantage of maintaining and enhancing resources (such as satellites) in their operational environment [68].

9. Conclusion

Satellite manufacturers and operators can apply smart maintenance strategies by leveraging advancements in software and technology to increase the sustainability of their activities. This paper demonstrated that much of the necessary technology is already available and successfully utilized in comparable products and other industries. Implementing smarter maintenance solutions can increase space sustainability and also opens new avenues to generate revenue. These solutions can help reduce manufacturing costs, increase the overall revenue per satellite, and enables the collection of detailed satellite health data, which can be used to further optimize manufacturing and maintenance activities. With significant advancements in machine learning and IoT sensor technologies, satellite operators can access more detailed information about their assets and use it to make better operational decisions. Research in the areas of distributed machine learning and edge computing can further enhance these processes and potentially enable a new approach to smart maintenance for satellites. Future research should investigate effective practices for adopting smart maintenance strategies from industries such as aviation to enhance satellite health operations. Additionally, long-term space missions, especially those involving human presence, introduce unprecedented challenges and new set of requirements for maintenance operations that need to be explored. Furthermore, investigating the requirements to establish a circular economy in space seems vital for safeguarding a sustainable and long-term use of space as a critical resource.

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