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An Integrated Framework for Electronic Health Monitoring and Remaining Useful Life Estimation in Small Satellites

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Abstract: The increasing reliance on nanosatellites and CubeSats for Earth observation, communication, and deep-space research has exposed the critical vulnerability of their onboard electronic systems to harsh space environments, including radiation, thermal cycling, and power fluctuations. Traditional telemetry monitoring relies on reactive, threshold-based methods that detect faults only after abnormal conditions manifest, often missing gradual degradation trends that lead to unexpected mission failures. To address this limitation, this paper proposes a lightweight, telemetry-driven predictive maintenance framework specifically designed for resource-constrained nanosatellite electronics. The proposed hybrid architecture combines onboard sensing, basic signal processing, and feature extraction with advanced ground-based predictive analytics. The system monitors key parameters, PCB temperature, bus voltage, current, battery status, and radiation exposure, to construct a unified Health Index (HI) that provides a comprehensive assessment of electronic health. Furthermore, the framework incorporates degradation trend analysis, Remaining Useful Life (RUL) estimation, and a digital twin environment to forecast system failures and enable proactive maintenance decisions. By shifting from reactive threshold monitoring to predictive intelligence, this framework aims to enhance the operational reliability, mission success rates, and lifespan of future CubeSat and nanosatellite missions.

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1.Introduction

Nanosatellites and CubeSats are now used for Earth observation, communication, scientific research, and deep space technology demonstrations. The small size and low cost and short development time of these satellites make them suitable for use by universities and research organizations. The electronic systems inside nanosatellites must operate at their maximum performance capacity because of the system restrictions on mass and power and volume. The space environment causes these electronic components to experience radiation and thermal cycling and vacuum conditions and continuous power fluctuations. The various stress factors will continue to damage components which include voltage regulators and batteries and processors and communication modules. The satellite requires built-in reliability improvements because physical repairs become impossible after it reaches orbit.

The standard method for satellite health monitoring depends on analyzing telemetry data through established threshold values. The ground station receives temperature and voltage and current data which triggers alarms when these parameters exceed their designated thresholds. The method used in this system offers simplicity and popularity but functions as a reactive solution. It detects faults only after abnormal conditions appear, which may already indicate partial damage. Small and gradual degradation trends, such as slow voltage drift, increasing current ripple, or progressive temperature rise, often remain unnoticed because they stay within safe limits for

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long periods. The unexpected nature of nanosatellite failures leads to mission failures which decrease operational reliability and shorten mission durations.

The research presents a predictive maintenance system which uses telemetry data to monitor nanosatellite electronics. The proposed method tracks temperature and voltage and current behavior and radiation exposure through time by examining their relationships over extended periods. The unified Health Index model provides a measurement system for the electronic system's health status while time-series prediction methods enable estimation of system degradation which will lead to critical failures. The system uses lightweight onboard monitoring together with sophisticated ground-based forecasting methods which makes it appropriate for CubeSat systems with limited resources. The proposed system uses predictive intelligence to replace reactive monitoring which will enhance mission success rates while increasing the operational lifespan of nanosatellite systems.

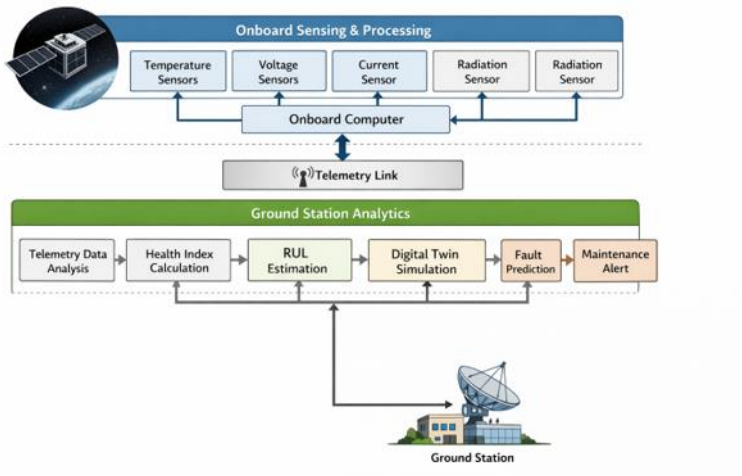


Figure 1. Proposed Telemetry-Driven Predictive Maintenance Architecture for Nanosatellite Electronics.

2. Related Works

2.1 Traditional Telemetry and Monitoring Methods

Satellite health monitoring systems operate through two main components which have used basic telemetry methods and threshold assessment methods throughout their history. The system continuously tracks electrical and environmental conditions through its onboard sensors which monitor parameters including temperature and voltage and current and battery level and processor status. The system sends telemetry frames which contain these values to the ground station at scheduled times. The engineers analyze this data by measuring it against specific operational thresholds which they have established. The system creates an alert when a monitored parameter goes beyond its safe limit which enables operators to implement corrective measures. The method provides three advantages to early CubeSat missions because it operates with basic processing needs while delivering dependable results through its efficient design.

Standard monitoring systems operate as reactive systems which do not possess predictive capabilities. The systems detect abnormal conditions only after they have reached a level which can be measured. The measured values stay within acceptable limits to detect small degradation trends such as gradual voltage drift and increasing current ripple and slow thermal rise. The process leads to unexpected failures which happen without any early warning signs. The traditional systems approach each parameter assessment as a separate task because they fail to investigate how temperature and radiation exposure and electrical instability interact with each other. The monitoring system uses threshold-based monitoring to maintain basic operational safety, but it fails to deliver health forecasting and remains useful life assessment for nanosatellite electronic subsystems.

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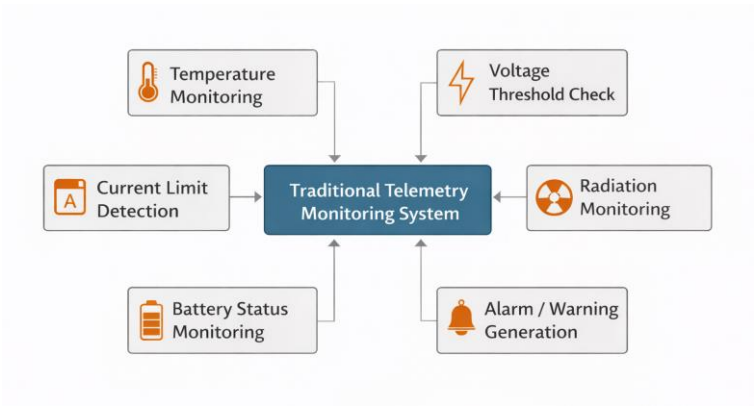


Figure 2. Traditional Telemetry Monitoring Framework for Satellite Electronics.

2.2 Fault Detection and Isolation in Spacecraft

Fault Detection and Isolation (FDI) systems operate on spacecraft to enhance their operational dependability and mission protection. The systems work to detect unusual operational patterns which occur in power systems and communication systems and attitude control systems and onboard computer systems. Most spacecraft use fault detection methods which compare real-time telemetry data against expected operational ranges or predefined system models. The system uses fault detection to identify the problematic component while it stops the issue from affecting other subsystems. The common practice of using redundancy involves using a backup system which automatically takes over when the primary system fails to ensure mission continuity.

The FDI techniques strengthen system reliability through their fault identification capabilities, yet they focus on post-fault detection instead of preemptive fault detection methods. The methods which isolate components use either rule-based systems or signal consistency assessments or model-based residual analysis techniques. The methods successfully identify instant failures which cause short circuits and sensor errors however their performance decreases when applied to identify slow electronic material degradation. Advanced predictive FDI systems remain uncommon in nanosatellites because of their strict power and computational limitations. The need exists for lightweight predictive systems which enable early detection of degradation points that lead to critical system failures.

2.3 AI-Based Predictive Maintenance in Aerospace

The aerospace industry has implemented artificial intelligence together with machine learning techniques for predictive maintenance purposes during the last few years. Commercial aircraft systems use large volumes of operational data to predict component wear, engine degradation, and system failures before they occur. Researchers use time-series analysis together with neural networks and support vector machines and decision-tree models to examine temperature and vibration and pressure and electrical signal patterns. The Remaining Useful Life (RUL) estimation concept provides algorithms that predict how long a component will function before it reaches its failure point. The approaches assist organizations in decreasing unexpected equipment outages while they enhance operational safety and decrease their maintenance expenditures.

Most AI-based predictive maintenance systems require aircraft or large satellites because these systems need intense computational power and they need to maintain constant ground connectivity. Nanosatellite operations have become difficult because strict power limits exist together with reduced onboard memory capacity and temporary communication periods. Existing research primarily investigates mechanical systems which include engines and rotating machinery, instead of studying low-power satellite electronic components. The research field lacks studies about lightweight telemetry-driven predictive maintenance systems that focus on nanosatellite electronic subsystems. To achieve effective predictive frameworks that need fewer resources, organizations must develop systems that can function under CubeSat resource limits.

2.4 Research Gap and Contribution of This Work

The existing research shows that traditional satellite monitoring systems use threshold-based telemetry assessment to monitor satellites while fault detection and isolation methods need to wait for outages to happen before they can identify malfunctions. The use of artificial intelligence methods for predictive maintenance in aircraft and large aerospace systems has proven effective yet these methods do not extend to nanosatellite electronic subsystems. Existing methods either need extensive computing power, or they focus on mechanical

systems instead of low-power space electronics. CubeSat systems need a complete framework that includes multiple telemetry analysis methods, degradation trend prediction, and remaining useful life assessment.

The paper presents a telemetry-based predictive maintenance system that has been developed specifically for nanosatellite electronic systems. The proposed approach uses an integrated Health Index model, which measures temperature and voltage, current and radiation exposure as one single unit. The system uses lightweight onboard monitoring together with advanced ground-based predictive analytics and digital twin simulation to create a hybrid architecture. The proposed system uses early degradation detection to forecast failures which help but conventional methods monitor systems after they start to show problems.

3. Proposed System Architecture

The overall structure of the proposed telemetry-driven predictive maintenance framework for nanosatellite electronics system is shown in this section. The system functions through a hybrid monitoring system which integrates onboard sensors and preprocessing systems with sophisticated predictive analytics that operate from ground facilities. The description of the onboard sensing and data acquisition system begins with its explanation. It detects vital electrical and environmental conditions through measurement of six specific parameters which include temperature and voltage and current and battery condition and radiation exposure. The onboard processing system uses its feature extraction methods to conduct basic filtering and trend observation and produce telemetry packets while following strict power and computational limits. The section then discusses the ground-based predictive analytics layer which uses telemetry data to create an integrated Health Index model and conduct degradation trend research and determine the remaining useful life of assets. The system response mechanism together with the maintenance decision process provides the ability to generate early warnings and establish plans for corrective actions. The resource-constrained nanosatellite platforms use these components to establish a complete predictive maintenance system which serves their operational needs.

3.1. Overall System Overview

The predictive maintenance system which we proposed consists of two primary parts which include an onboard component and a ground component which Figure 3 shows. The onboard segment handles all tasks which include detecting events processing initial data and sending telemetry information to other systems. The system works under the extreme limitations which protect the power resources and memory capacity and processing power of a nanosatellite system. The system continuously tracks all essential electronic measurements which include temperature and voltage and current and battery health and radiation exposure. The system performs basic preprocessing together with local anomaly detection which results in data handling efficiency before the data gets sent to other systems

The ground segment performs advanced predictive analysis through its analysis of received telemetry data. The ground infrastructure system exceeds onboard system performance because it possesses greater processing power and storage capacity which enables the execution of advanced modeling techniques. The telemetry-driven monitoring process starts when the satellite sensors collect measurements, and the data undergoes preprocessing before it is sent to the ground station through packet transmission. The data undergoes storage and analysis which results in the creation of a unified Health Index together with degradation trends assessment. The system operates as a hybrid intelligence framework which combines lightweight space monitoring with advanced predictive analytics that take place at ground facilities.

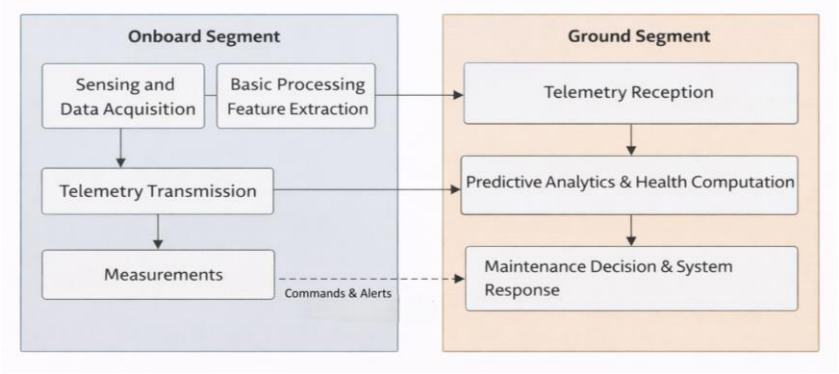


Figure 3. Proposed Hybrid Telemetry-Driven Predictive Maintenance Architecture for Nanosatellite Systems.

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3.2 Onboard Sensing and Data Acquisition

The onboard sensing and data acquisition layer continuously tracks the operational status of essential electronic systems which exist within the nanosatellite. The system gathers instant data from all sensors which are embedded in the power and processing units. The main goal of the project is to detect initial indications which indicate electrical instability and environmental conditions that will damage components. The nanosatellite sensing system needs to operate with minimum power requirements and compact design because the satellites have strict operational constraints. The system monitors only those parameters which directly impact the reliability of electronic systems.

The data acquisition process starts when sensors measure temperature and voltage levels and system current and battery condition and radiation exposure. The onboard analog-to-digital converter (ADC) which exists in the microcontroller or onboard computer system converts the analog signals into digital values. The system uses a specific sampling frequency which provides both accurate monitoring results and reduced power usage. The system temporarily keeps raw data after digitization to conduct basic preprocessing before the data enters telemetry packets. The system collects data in a structured manner which enables reliable monitoring while it meets the resource limitations of CubeSat satellites.

Table 1. Onboard Sensing Parameters for Electronic Health Monitoring

Parameter Monitored	**Sensor Type**	**Purpose**	**Importance for Predictive Maintenance**
PCB Temperature	Thermal sensor	Measures heat generated by electronics	Detects thermal stress and overheating trends
Bus Voltage	Voltage sensor	Monitors stability of power rails	Identifies voltage drift and regulator degradation
System Current	Current sensor	Measures total current consumption	Detects abnormal load changes and ripple increase
Battery Status	Battery monitoring circuit	Tracks battery voltage and charge level	Evaluates battery aging and power reliability
Radiation Exposure	Radiation sensor	Measures accumulated radiation dose	Correlating environmental stress with degradation

3.3 Onboard Processing and Feature Extraction

The onboard processing and feature extraction module performs initial analysis of the collected sensor data before transmission to the ground station. The current stage of the process handles only essential computations because nanosatellites have strict limitations on power and memory capacity. The system needs to achieve three goals which include reducing noise and identifying fundamental anomalies and extracting useful features from the raw telemetry signals. The system maintains continuous health monitoring while it uses system resources in an efficient manner.

After data acquisition, basic signal conditioning techniques proceed to process raw digital sensor values through their initial state by applying moving average filtering and threshold comparison methods. The methods successfully eliminate both measurement noise and short-term fluctuations that occur during the measurement process. The system calculates basic trend indicators which include temperature gradient and voltage drift rate and current variation index. The extracted features provide more valuable health indicators than the usage of raw values. The onboard processing workflow establishes its operations through four stages which begin with filtering and end with telemetry packet formation that transmits data to the ground segment according to Figure 4. The system prepares processed data together with anomaly flags into structured telemetry packets which will be transmitted. The system achieves data redundancy reduction and ground-based predictive analytics effectiveness improvement through its onboard feature extraction process.

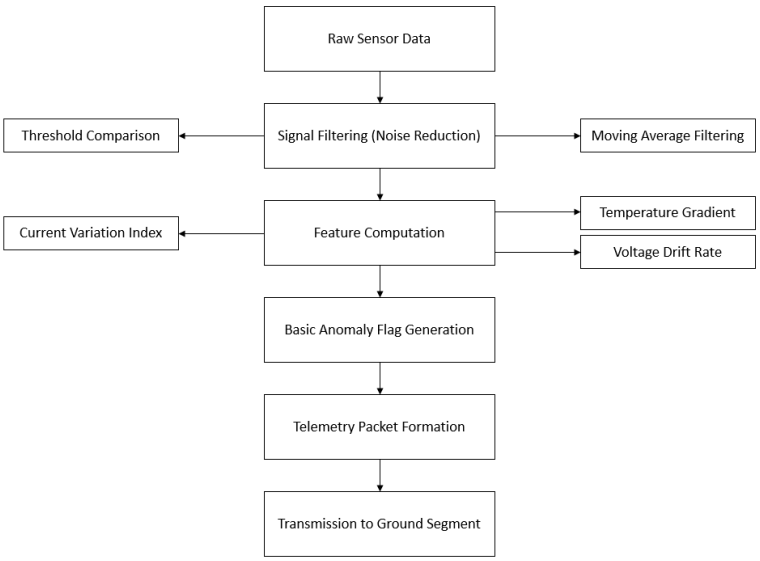


Figure 4. Onboard Data Processing and Feature Extraction Flow Diagram

3.4. Ground-Based Predictive Analytics

The main intelligence system of the maintenance framework uses ground-based predictive analytics as its central intelligence system. The ground station of the system possesses greater processing capabilities and storage capacity than the onboard segment. The satellite transmits telemetry packets which are first received and stored in a structured database used for long-term analysis. Time-stamped data contains all parameters, which include temperature, voltage, current, battery status, and radiation exposure, organized as a time-series dataset. The system stores historical data in a structured format which allows for both historical comparisons and tracking of extended period equipment deterioration.

After data storage, a unified Health Index (HI) is computed to represent the overall condition of the electronic subsystem. The Health Index uses normalized temperature variation, voltage drift, current instability and radiation exposure values to create a single measurement system. The integrated indicator enables better system health assessment and reduces monitoring difficulties. The Health Index system updates constantly because new telemetry data arrives, which enables ongoing health assessment throughout the mission.

Trend analysis is then performed to detect gradual degradation patterns. Statistical techniques such as moving averages slope estimation and variance tracking enable researchers to identify slow changes which do not exceed threshold limits yet show signs of progressive aging. The researchers apply time-series modeling methods to forecast upcoming developments in essential parameters. The models use historical telemetry data to forecast system variable changes throughout upcoming time periods. The system detects upcoming instability by predicting parameter trends which enables the system to prevent critical system failures.

The layer requires Remaining Useful Life (RUL) estimation as its vital element. The system calculates the operational time that will pass before a parameter reaches its critical limit by using both the degradation rate and the historical data. The system enables maintenance teams to schedule their work according to anticipated issues instead of waiting for actual faults to occur. The ground station uses a digital twin model which represents the electronic subsystem of the system. The digital twin operates as a virtual copy that receives constant updates through actual telemetry information. The digital twin enables organizations to assess future operational situations which leads to better understanding of system degradation and more precise prediction results. The combination of these predictive methods enables maintenance teams to derive usable maintenance intelligence from unprocessed telemetry data.

3.5. Maintenance Decision and System Response

The maintenance decision and system response layer converts predictive insights into actionable operational commands. The proposed framework uses prediction outputs such as Health Index trends and Remaining Useful Life estimates to trigger early maintenance strategies, which differ from conventional telemetry systems that only generate alerts after a parameter exceeds a limit. The system uses ground-based predictive analytics to detect abnormal degradation patterns, which allow it to assess severity levels and select suitable corrective actions.

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The first level of response includes warning generation, which sends early alerts to mission operators when system degradation reaches its established risk limits. Engineers use these warnings to evaluate system conditions that will lead to critical faults. The next stage of degradation lets engineers use load adjustment methods, which include processor workload reduction, payload operation time limits and power distribution optimization. In power rail or subsystem instability situations, controlled power cycling will be used to reset components while restoring system stability.

The system recommends safe mode activation, which disables non-essential subsystems to maintain essential system operations during more critical conditions. The system uses backup switching mechanisms to replace a failing unit through its hardware redundancy features when hardware components become operational. The structured response hierarchy enables the predicted system framework to execute predictive maintenance instead of performing only passive monitoring. The system improves nanosatellite reliability and prolongs mission duration through its direct link between analytics and operational control decisions Fig.5.

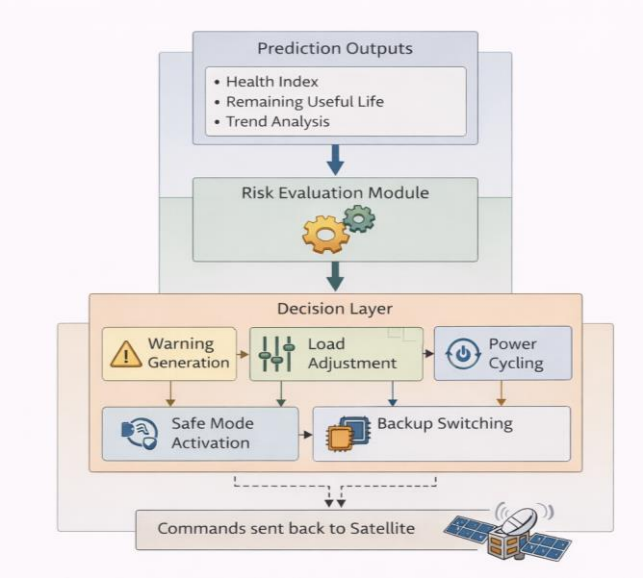


Figure 5. Predictive Maintenance Decision and System Response Framework for Nanosatellite Electronics.

4.Health Modeling and Mathematical Framework

This section provides the mathematical background of the proposed predictive maintenance framework. It defines the why and how of the formulation of a unified Health Index that combines a set of telemetry parameters into a single quantitative indicator of the state of an electronic system. The section also presents the normalization method used to convert the various parameters to a similar range, hence enabling uniform comparison and equal contribution of the Health Index. In addition, the procedure for parameter weight factors determination is described to reflect the importance of temperature, voltage, and current behavior, as well as the effect of radiation exposure. Finally, a degradation modeling approach is introduced to estimate the health evolution of the system over time and compute the remaining useful life of the electronics subsystem. These mathematical components form a scientific base for predictive maintenance decision-making in a structured manner.

4.1. Health Index Formulation

Accordingly, a unified Health Index (HI) is introduced for the quantitative evaluation of the condition of nanosatellite electronic subsystems. Combining into a single number the information obtained during the joint processing of several telemetry parameters makes it possible to perform an integrated assessment of the health of the nanosatellite electronic subsystems. Instead of dealing with the temperature, voltage, current behaviour, and the radiation exposure separately, the proposed framework attempts to combine them and provide one metric that is measurable. This uniform representation provides for the simplification of health monitoring and makes possible the provision of the discrete degradation under the entire mission duration.

4.2. Health Index Calculation

The Health Index (HI) is calculated by combining the normalized telemetry parameters into a single numerical value that represents the overall condition of the nanosatellite electronic subsystem. Since temperature, voltage,

current, and radiation exposure have different measurement units and operating ranges, their values are first normalized to maintain a common measurement scale. This process allows the system to evaluate different electronic parameters together.

The normalization process converts the collected sensor measurements into a standard range based on their defined operating limits. Each parameter is evaluated according to its deviation from normal operating conditions. For example, an increase in PCB temperature, variation in bus voltage, abnormal current consumption, or higher radiation exposure may indicate possible degradation of electronic components. The normalized values help identify these changes and make them suitable for combined health assessment.

After normalization, individual degradation indicators are combined using assigned weight factors. These weight factors represent the relative importance of temperature, voltage, current, and radiation exposure in determining the overall condition of the electronic subsystem. The selection of these factors depends on component specifications, operating conditions, and mission requirements. Their combined contribution provides a unified assessment of the satellite's electronic health.

The calculated Health Index is represented on a scale from 0 to 100. A higher value indicates better electronic subsystem health, whereas a decreasing value represents increasing degradation. The ground station continuously updates the Health Index whenever new telemetry measurements are received from the satellite. By examining changes in the index over time, the system can identify gradual deterioration even when individual telemetry parameters remain within their predefined operating limits.

This approach provides a simplified method for evaluating the overall health of nanosatellite electronics. The calculated Health Index also serves as an important input for degradation trend analysis, Remaining Useful Life estimation, and predictive maintenance decision-making.

4.3. Remaining Useful Life Estimation

Remaining Useful Life (RUL) estimation is an important part of the proposed predictive maintenance framework, as it helps estimate the remaining operational period of nanosatellite electronic components before they reach their critical degradation condition. The estimation is performed by analysing the historical Health Index values and identifying the rate at which the electronic subsystem health decreases over time. The ground-based analytics system examines changes in temperature, voltage, current, and radiation exposure to identify continuous degradation patterns. Based on these observations, the system estimates the possible time before the Health Index reaches its predefined critical level. This information helps engineers identify components that may require attention and plan suitable operational adjustments before serious failures occur. The RUL estimation process therefore supports early fault prediction, improves maintenance planning, and helps increase the operational reliability of nanosatellite electronic systems.

5. Expected Performance and Applications

The proposed telemetry-driven predictive maintenance framework is expected to improve the monitoring and reliability of nanosatellite electronic subsystems through continuous analysis of telemetry data. By combining temperature, voltage, current, battery condition, and radiation exposure measurements, the system provides a unified assessment of electronic health. The Health Index and degradation trend analysis help identify gradual changes in component behaviour before they reach critical operating limits. This approach is expected to provide earlier indications of possible electronic failures compared with conventional threshold-based monitoring methods. The use of onboard preprocessing and ground-based predictive analytics also helps maintain an efficient balance between computational requirements and monitoring capabilities.

The proposed framework has potential applications in CubeSats, university-built nanosatellites, Earth observation missions, communication satellites, and other small spacecraft platforms. It can be used to monitor important electronic components such as power distribution units, voltage regulators, batteries, onboard computers, and communication modules. The system can also support mission operators in evaluating subsystem conditions and identifying components that may require further investigation. Based on the predicted degradation trends, suitable operational adjustments can be planned to reduce unnecessary stress on electronic components and maintain essential satellite functions.

Another important application of this framework is its potential integration with future satellite health management systems and digital twin environments. Historical telemetry data can be used to improve degradation prediction models and support more accurate Remaining Useful Life estimation. The framework can also be extended through machine learning techniques to identify complex relationships between different operating

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parameters. Although actual performance requires validation using simulated or real satellite telemetry datasets, the proposed architecture provides a foundation for developing lightweight predictive maintenance solutions for resource-constrained nanosatellite missions.

6.Limitations and Future Scope

The proposed telemetry-driven predictive maintenance framework provides an approach for monitoring the health of nanosatellite electronic subsystems. However, certain limitations need to be considered during its development and implementation. The accuracy of degradation prediction depends on the availability and quality of historical telemetry data. Limited access to long-duration satellite datasets may affect the evaluation of prediction models. Sensor accuracy, calibration errors, communication interruptions, and variations in operating conditions can also influence the reliability of health assessment. Furthermore, nanosatellites have limited onboard processing capacity, memory, and power availability, which creates additional challenges for implementing advanced monitoring techniques.

Future development of the proposed framework can focus on testing the architecture using simulated telemetry datasets and actual nanosatellite operational data. Machine learning techniques can be integrated to improve the identification of abnormal operating patterns and predict gradual electronic degradation. The Health Index model can also be improved through component-specific parameters and suitable weight selection based on experimental observations. Further development may include improved Remaining Useful Life estimation and digital twin integration to study electronic subsystem behaviour under different operating conditions.

The framework can also be extended through hardware-based testing and long-term validation using representative satellite electronic components. Experimental evaluation of temperature, voltage, current, and radiation-related variations can help determine the accuracy and reliability of the proposed monitoring approach. Integration with ground station software and existing satellite telemetry systems may further support practical implementation. These developments can help establish a lightweight and reliable predictive maintenance framework for future CubeSat and nanosatellite missions.

7.Conclusion

This paper presents a telemetry-driven predictive maintenance framework for monitoring and evaluating the health of electronic subsystems in nanosatellite applications. The proposed approach combines onboard sensing, data acquisition, feature extraction, and ground-based predictive analytics to identify early signs of electronic degradation. By monitoring important parameters such as temperature, voltage, current, battery condition, and radiation exposure, the framework provides a comprehensive assessment of satellite electronic health. The integration of a unified Health Index enables multiple telemetry parameters to be evaluated through a common health assessment method, while degradation trend analysis supports the identification of gradual changes in component behaviour. Furthermore, Remaining Useful Life estimation provides an approach for predicting the possible operational period of electronic components before they reach critical degradation conditions. The proposed hybrid architecture also considers the limited power, memory, and computational resources available in nanosatellite platforms by performing basic data processing onboard and advanced analysis at the ground station. The integration of predictive analytics with a digital twin environment offers additional possibilities for understanding electronic subsystem behaviour under different operating conditions. Unlike conventional threshold-based monitoring approaches, the proposed framework focuses on identifying potential degradation trends before critical operating limits are reached. Although experimental validation using simulated or actual satellite telemetry data is required to evaluate its prediction accuracy and practical performance, the proposed architecture establishes a foundation for developing intelligent health monitoring solutions for small spacecraft. Future improvements involving machine learning, hardware testing, and long-duration telemetry analysis may further enhance its capabilities. Overall, this framework provides a potential approach towards improving electronic subsystem reliability, supporting mission planning, and increasing the operational dependability of future CubeSat and nanosatellite missions.

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9.Conflict of Interest

The author declares no competing conflict of interest.

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