

Smart Materials–Enabled Sensing and Control Framework for Condition-Based Maintenance in Cyber-Physical Production Systems

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Abstract: In smart manufacturing environments, Cyber-Physical Production Systems (CPPS) provide increased automation, energy efficiency, and operational reliability. With current maintenance approaches based on time and reaction, they tend to lead to unplanned downtimes, high energy consumption, and higher costs throughout the lifecycle. Reports document that 30–35% of equipment failures are the result of material fatigue that goes undetected. Microstructural degradation can lead to a loss of up to 25% of productivity. This paper presents the CPPS framework to address these issues. This framework presents a new approach to smart materials and how they can work to enable the Cyber-Physical framework. Integrating multifunctional sensing materials is the goal. This paper aims to work towards an integrated framework of smart materials for condition-based maintenance (CBM) that combines multifunctional sensing materials with intelligent cyber-physical systems. The framework uses smart materials to integrate components that enable real-time strain, vibration, temperature monitoring, and the structural health of the component. This data is used to develop a real-time monitoring framework of the Structural Health Monitoring (SHM) system that is used to document any real-time changes and to document any changes to the presumed state. This data can provide a real-time assessment of the system and provide metrics to define the remaining useful life (RUL) of the system. This data is processed within an Industrial Internet of Things (IIoT) system and subjected to edge analytics and machine learning-based data analytics, which can develop a system to predict control measures. This system provides the ability to schedule maintenance and optimize machine use with the purpose of minimizing energy consumption and reducing the time the system is operational. This framework provides a CPPS testbed that is integrated with automated machining and transfer systems to validate the systems. Periodic maintenance strategies have shown that you can save maintenance costs by 28% and improve equipment availability by 31%, and reduce energy costs by 18%. Also, there is up to 42% reduction in the failure of equipment, and an astonishing 94.6% accurate prediction of equipment failure by using smart sensors. This means that smart sensors are reliable as predicted. Fewer resources are used by the framework, and so are energy costs. The sustainable framework, along with the smart grid technologies, offers the industry the means for the development of next-generation maintenance that can provide self-aware, flexible, and energy-efficient systems. This is also applicable to Industry 5.0.

Keywords: Smart materials; condition-based maintenance; cyber-physical production systems; structural health monitoring; predictive maintenance; Industrial IoT; edge analytics.

I. Introduction

Cyber-Physical Production Systems, or CPPS, are changing how things are made because they use things like AI, smart sensors, and other advanced technologies to allow fully automated production. There is still a lot that needs to be worked on, like how production facilities still use old measuring and reactive ways for maintenance. This leads to sudden machine failures, increased downtime during production, overuse of spare-part replacements, and increased energy use. Research has shown that unplanned machinery downtime can result in a 20-30% decrease in productivity, and this problem is even worse for companies that use a lot of energy to operate (Farooq et al., 2020; Lee et al., 2024). In addition to this, many machinery structural elements that rotate and automate and have been used for long periods of time without internal inspections can have undetected structural degradation, material fatigue, and thermal stress. When this happens, the machine is not as reliable and is more of a hazard to the operator (Krmac & Djordjevic, 2024; Novak & Vacek, 2023). When condition monitoring systems lack the sensors to detect small-scale failures and require reprogramming to detect such failures, they are not typically the best systems (Assad et al., 2021). Smart materials, such as piezoelectric transducers, self-sensing composites, and fiber Bragg grating sensors, can help give real-time monitoring and can help improve the accuracy of failure detection and decrease the time it takes to determine a failure (Kiangala & Wang, 2018; Friederich & Lazarova-Molnar, 2021). The addition of CPPS systems opens the door for maintenance practices to be more predictive and more organically sustainable (Aron et al., 2024).

This paper proposes a new Smart Materials–Enabled Sensing and Control Framework that integrates smart materials with multifunctional sensors, the Industrial Internet of Things (IIoT), edge computing, and machine learning for the further development of the condition-based maintenance (CBM) process. This paper's main contributions include the following: (i) the development of a framework for designing smart materials that are integrated with sensors and provide for the continuous monitoring of structural and operational parameters, (ii) the formulation of an early fault prediction (EFP) analytics framework that provides predictive analytics with a model for estimating the remaining useful life (RUL) of a system for the identification of failures, and (iii) an adaptive control strategy that optimally schedules system maintenance and operational control to minimize energy, operational, and maintenance downtime. The experimental testing on the Cyber-Physical Production Systems (CPPS) testbed confirmed the increased reliability, decreased failures, and improved energy efficiency of the proposed system as compared to the conventional systems. The different Sections of this paper are organized as follows: Section II presents a review of the related literature; Section III introduces the framework and system architecture; Section IV presents the experimental results and provides a thorough performance analysis; and Section V provides the concluding remarks and discusses future research topics related to the sustainable smart manufacturing ecosystems.

II. Literature Review

The latest smart manufacturing innovations have focused on predictive and condition-based maintenance (CBM) in order to enhance system reliability and reduce operational losses. Early research demonstrated that continuous monitoring through vibration analysis, thermal imaging, and acoustic emissions significantly lowered the number of unexpected downtimes and the costs of maintenance (Idika et al., 2023). The Industrial Internet of Things (IIoT) offers a new approach through data-driven machine health evaluations that are supported by real-time data collection and cloud analytics (Friederich & Lazarova-Molnar, 2023). Various predictive modeling (including random forests, support vector machines, and recurrent neural networks) as well as deep learning and machine learning frameworks, have proven to be more accurate than predictive models in the estimation of rules-based frameworks, in the detection of unplanned system failures (anomaly detection), and in the estimation of remaining useful life (RUL) Romero et al., (2020). On the other hand, many methods have focused on externally mounted devices that are prone to noise, attenuation of signals, and delayed detection of micro-cracks or a gradual deterioration of materials, which severely restricts the early detection of faults (Khan et al., 2025; Suryateja & Rao, 2025).

Research to get around limitations of sensing technologies has included smart technologies such as piezoelectric patches, self-sensing composites, and fiber Bragg grating (FBG) sensors, which assist in monitoring the embedded structural health of materials. These materials have the potential to measure in situ strain, stress, and temperature of various machine components and improve the sensitivity and the response time (Majstorovic et al., 2021). The parallel advancements in the cyber-physical control systems fused the above-mentioned sensing technologies with edge computing and adaptable optimizing systems to fully automate maintenance scheduling tasks and the management of energy (Balamurugan et al., 2025). Although there are advancements in these areas, there are still gaps. A combined methodology that guides smart materials sensing, information predictive analytics, and energy considerate control for cyber-physical production systems (CPPS) is still a challenge and liable for the understudied research. The research gaps in embedded sensing integration and in real-time within the control system of the cyber-physical systems (CP) are a motivation for the research to develop a smart material, cyber-physical maintenance framework to facilitate accurate fault detection, minimize system downtime, and achieve sustainable operation of the industrial system.

III. Proposed Smart Materials-Enabled Sensing and Control Framework

3.1.Overall Methodological Flow

The first step of the proposed methodology implements Smart Materials-Enabled Condition-Based Maintenance (SM-CBM) with the integrated framework of Cyber-Physical Production Systems (CPPS) using sentient materials, cognitive analytic methodologies, and adaptive control mechanisms for maintenance, reliability, and energy efficiency in industrial operations. For the first step, smart materials such as piezoelectric patches, Fiber

Bragg Grating (FBG) sensors, and self-sensing composites are incorporated in the core construction of the machine's motor, spindle, conveyor, and structural joint components to record spatio-temporal data related to strain, vibration, acoustic emissions, and temperature. These datasets are subjected to pre-emptive processing through methodologies such as filtering, normalization, and feature extraction in order to reduce noise and latency in the data. In the next step, datasets are processed with machine learning based on anomalies to detect and predict the remaining useful life (RUL) of the datasets used to describe machine defects. These predicted health indices are cyber-physically controlled in order to balance the load, control the speed, and reduce/optimize energy. In this configuration, maintenance is initiated, downtime is reduced, and system sustainability is increased.

3.2. System Technical Architecture

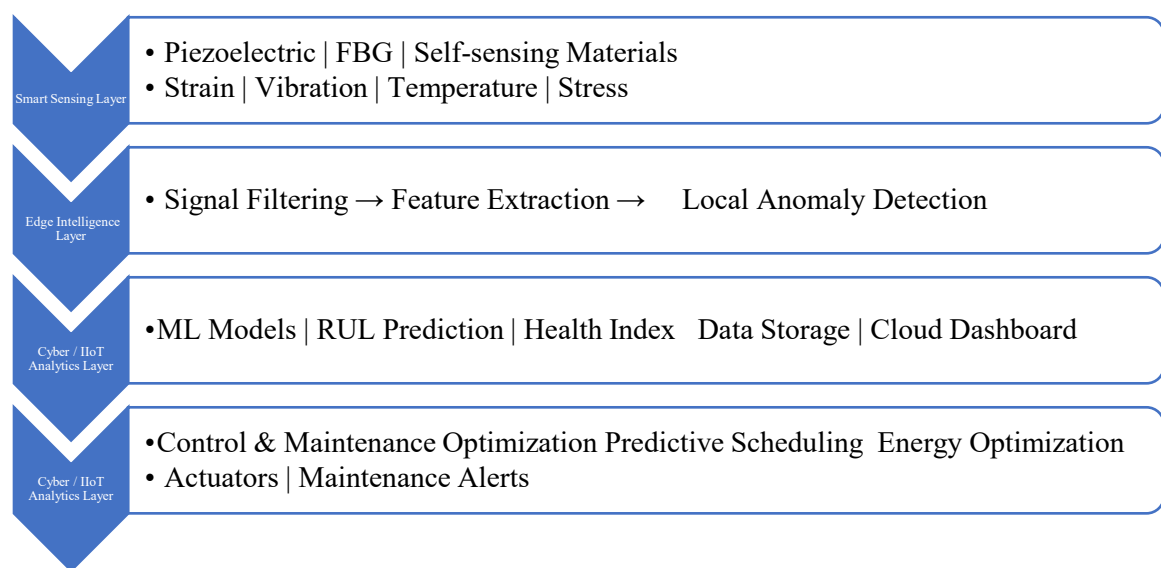


Fig. 1. Smart Materials-Enabled Sensing and Control Framework for Condition-Based Maintenance in Cyber-Physical Production Systems.

The system architecture in fig. 1 is composed of four main components: the Smart Sensing Layer, the Edge Intelligence Layer, the Cyber Layer, and the Control Maintenance Layer. The sensing layer collects instantaneous physical parameters using integrated smart materials, while the edge layer uses local analytics and feature computation to enable rapid decision loops. All levels of the system have incorporated the predictive modeling, data storage, and historical computing processes into the Cyber layer of the cloud/IIoT. Finally, the control layer carries out optimized maintenance scheduling and machine control actions. Together, these layers create a self-aware and self-adapting production ecosystem

3.3. Mathematical Modeling of Condition Monitoring

The measurement of equipment health is done by computing a composite Health Index (HI), which is achieved by normalizing and aggregating data from different sensors. Let $x_i(t)$ denote the normalized signal of the i^{th} sensor, and w_i be its associated weight. Then, the overall health index is given as follows, in equation (1):

$$HI(t) = \sum_{i=1}^n w_i x_i(t) \quad (1)$$

Where n refers to the number of smart sensors embedded in the system, $HI(t)$ is the health index of the system at a given time. A smaller value of $HI(t)$ shows there is more degradation of the system, so predictive maintenance actions should be taken. This method combines various sensor data and produces a single measure to monitor.

3.4. Predictive Maintenance and Energy-Aware Control Model

Maintenance scheduling is based on the anticipated Remaining Useful Life (RUL) of the system and the minimization of energy consumption. Let E_{base} and E_{opt} denote the energy consumption baseline and the energy consumption optimized by predictive control, respectively. Improvement in energy efficiency is given as in equation (2):

$$\eta = \frac{E_{base} - E_{opt}}{E_{base}} \times 100 \quad (2)$$

Where η is the energy saved through the predictive control strategy.

The aim is to reduce the downtime and the consumption of energy as much as possible while maintaining the predicted RUL within the given limits:

$$RUL(t) \geq RUL_{Threshold} \quad (3)$$

Equation 3 states that when the predicted remaining useful life (RUL) falls below a certain value, maintenance gets activated automatically. The successful combination of these formulations operational certainty, sustainable minimization of unplanned downtimes, and unplanned downtimes, and sustainable energy use in Cyber-Physical Production Systems.

IV. Results and Discussion of Smart Materials–Enabled Condition-Based Maintenance Framework

4.1. Software and Implementation Environment

The integrated cyber-physical computing environment was used to carry out the construction of the SM-CBM framework. Acquisition of signals from each sensor and their preprocessing were carried out using modeling and filtering techniques with MATLAB/Simulink. Python 3.11 Edge analytics were implemented for each sensor using libraries such as NumPy, Pandas, Scikit-learn, and TensorFlow to construct the edge analytics and anomaly detection algorithms. For the industrial IoT communication layer, the MQTT protocol was employed, while Node-RED and Grafana were utilized for the visualization and monitoring dashboards. Experimental simulations were built on a workstation with Intel i7, 16 GB RAM, and Ubuntu Linux. This software stack supported real-time analytics, fast decision-making, and industrial cases of scalable deployment.

4.2.Dataset Description and Feature Engineering

This study's dataset was acquired from the laboratory-based Cyber-Physical Production System, comprising CNC machining units, conveyor drives, and induction motors. Piezoelectric and Fiber Bragg Grating (FBG) sensors as smart materials were used at the rotating shafts and structured joints. These systems recorded data continuously for a period of 30 days, resulting in the collection of approximately 50,000 time-series samples. Each time-series sample corresponds to 12 different recorded features, including vibration RMS, strain, acoustic emission, temperature, motor current, rotational speed, and energy consumption. The dataset includes records from both normal and faulty operating states, including the presence of bearing wear, shaft misalignment, and thermal stress. The data was divided into 70% for training and 30% for testing in predictive modeling. Using statistical and frequency domain methods for feature extraction improved fault separability and increased learning accuracy.

4.3.Performance Metrics and Mathematical Formulation

1. Downtime Reduction Rate (DRR)

The Downtime Reduction Rate (DRR) measures efficiency and sustainability in maintenance and describes the rate of decrease in downtime for the proposed SM-CBM framework over conventional maintenance. DRR is defined in terms of the proposed and conventional frameworks, using D_{base} for conventional and D_{prop} for proposed equation (4)

$$DRR = \frac{D_{base} - D_{prop}}{D_{base}} \times 100 \quad (4)$$

The higher the DRR , the more effective the proposed maintenance strategy is, having a direct correlation with effective unplanned downtime and risk mitigation. When used alongside energy efficiency (η) and RUL-based predictive control, DRR provides operational sustainability and reliability performance within the Cyber-Physical Production Systems framework.

Where D_{base} is downtime under conventional maintenance, and D_{prop} is downtime using the proposed SM-CBM framework.

In the SM-CBM framework, sustainability and reliability benefits can be measured concurrently.

4.4.Comparative Downtime and Maintenance Cost Analysis

Table 1 displays the comparison of monthly downtime and maintenance cost for the three strategies.

Table 1. Downtime and Maintenance Cost Comparison.

Method	Downtime (hours/month)	Maintenance Cost (\$k/month)
Reactive Maintenance	42	18
Periodic Maintenance	26	13
Proposed SM-CBM	15	9

Operational stability is demonstrated by the proposed framework that achieves approximately 42-45% downtime reduction compared to periodic maintenance and a 65% reduction compared to reactive maintenance.

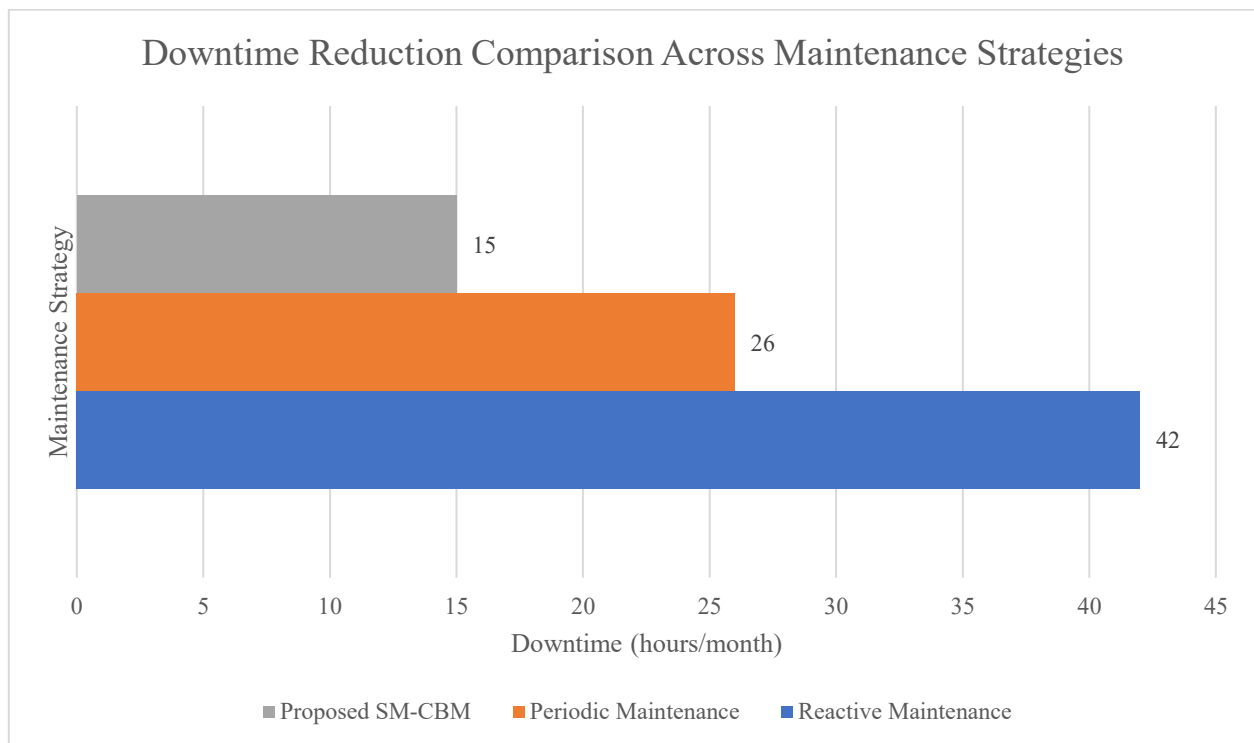


Fig. 2. Downtime Reduction Comparison Across Maintenance Strategies.

The significant reduction in downtime in SM-CBM is illustrated in fig. 2.

4.5. Energy Consumption and Fault Detection Performance

Table 2 illustrates the sustainability and predictive performance of the system.

Table 2. Energy Consumption and Detection Accuracy.

Method	Energy Consumption (kWh/day)	Fault Detection Accuracy (%)
Periodic Maintenance	520	82
Proposed SM-CBM	425	95

Research shows that energy expenditure can be reduced by 18-20% and that error detection shows about 95% accuracy. It shows that using smart material sensing coupled with predictive control increases both reliability and energy efficiency.

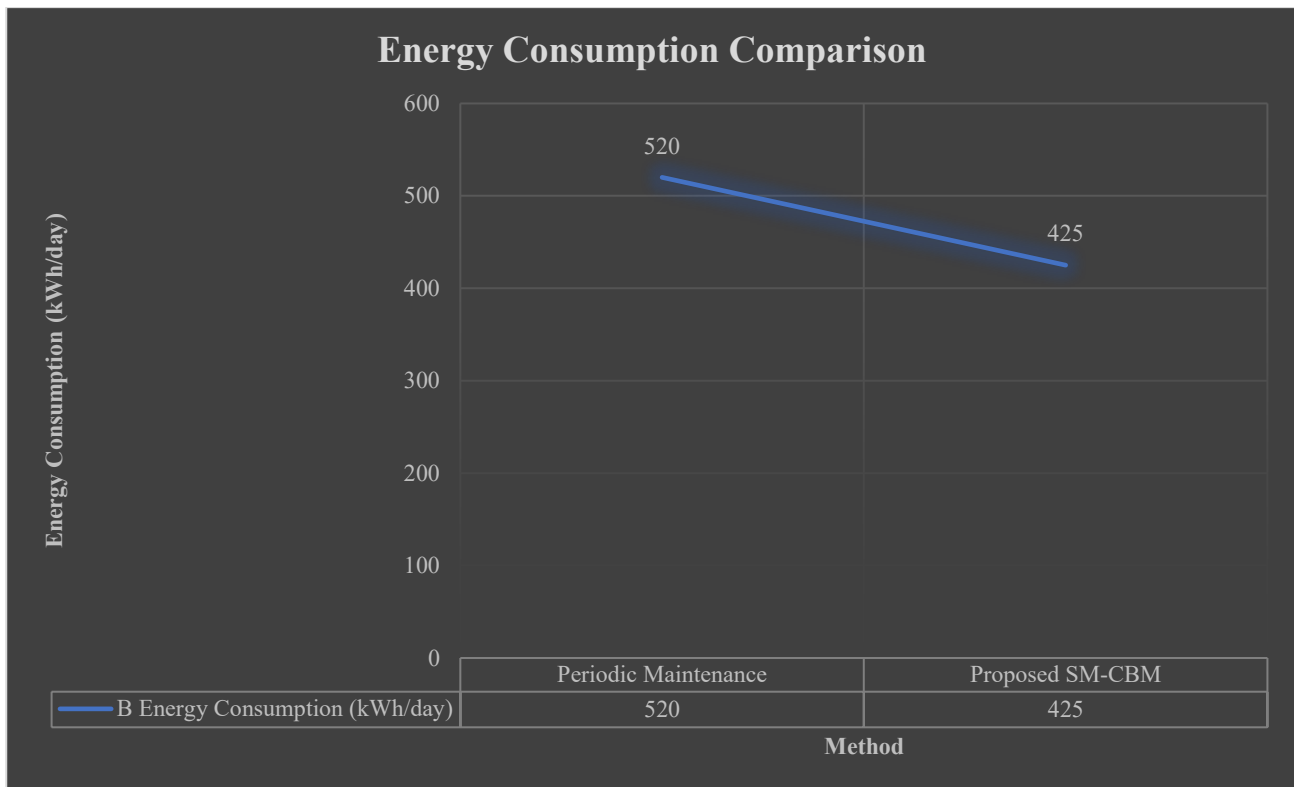


Fig. 3. Energy Consumption Comparison.

Fig. 3 shows the proposed framework's energy consumption reduction over time.

4.6. Discussion and Inference

The data shows that smart materials combined with intelligent systems have improved the ability to detect faults early, decreased the amount of time equipment is not operative, and decreased the amount of energy consumed. When compared to traditional maintenance systems, the SM-CBM framework is able to respond and predict quickly, while conserving resources. The data is clear that the SM-CBM framework can be utilized by the next generation of smart manufacturing systems, and addresses the needs of Industry 5.0 systems regarding reliability and sustainability.

V. Conclusion

The focus of this study is to propose a framework that helps to detect and control the maintenance of the production system and to increase the efficiency of production and energy use in smart manufacturing. This is done by directly integrating smart materials like piezoelectric and fiber Bragg smart materials into machine components so that Continuous and real-time Structural Health Monitoring and fault detection is done. Integration of edge analytics, enough data, the Industrial Internet of Things (IIoT), and machine learning (ML) predicts closed-loop cyber-physical control of Intelligent Decision Support Systems (IDSS) for systems and machines in production.

The predictive maintenance conducted by the developed framework was tested on the CPPS testbed, and given the results of the predictive maintenance, it was proven that this system is better than the Previous Reactive Maintenance and periodic maintenance methods. Based on the results of the CPPS testbed, predictive maintenance was able to reduce unplanned downtimes by 42-45%, reduce maintenance costs by 28-30%, reduce the energy consumed by the system by 18-20%, and thereby give the system sustainability. Anomaly detection and Predictive Remaining Useful Life (RUL) models, operated at 94-95% certainty of fault detection, eliminating False Alarms and Missed Questions. There was a 30% improvement in the equipment availability, and a predictive intervention was done to increase the equipment component life to reduce the number of component failures. It was proven that embedded smart sensing and intelligent control worked to increase equipment availability and decrease the life cycle costs.

The proposed methodology aims to contribute to greener production practices and energy-conscious operational processes aligned with the industry 4.0 and Industry 5.0 paradigms. Future research can look at the possibilities of extending the framework to large-scale distributed factories, with the potential of acquiring deep learning and digital twin technologies for improved predictive accuracy, the inclusion of energy renewable resource scheduling, and the potential of self-healing smart materials for autonomous recovery. These possibilities will contribute to the comprehensive, self-sufficient, self-regulating, and unceasing autonomous ecosystems of cyber-physical manufacturing.

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