IJARST

*International Journal of Advanced Research in Science and Technology*

https://doi.org/10.62226/ijarst20262759

ISSN 2319 – 1783 (Print)

ISSN 2320 – 1126 (Online)

# Smart Warp Tension Tracking Through Wireless Sensor Networks

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**ARTICLEINFO**

***Article history:***

| | |
|---|---|
| Received | 29 Jul 2026 |
| Accepted | 10 Aug 2026 |
| Available online | 21 Aug 2026 |

***Keywords:***

*Smart Textile Manufacturing, Wireless Sensor Networks (WSN), Edge Computing, Industrial Internet of Things (IIoT), Real-Time Error Detection and Warp Tension Monitoring.*

***Indexed in:***

doi Crossref

INDEX COPERNICUS INTERNATIONAL

Google scholar

*and in major libraries*

**ABSTRACT**

Preserving ideal warp tension is essential in contemporary textile production to ensure excellent material quality and prevent loom downtime. However, complex connection structures or infrequent hand testing are intrinsic to classic tension surveillance systems. Due to their absence of spatial adaptability and real-time responsiveness, these traditional approaches often result in undiscovered tension anomalies and thread breakages. This research presents a unique paradigm for investigating dynamic stress fluctuations using Smart Warp Tension Monitoring Using Wireless Sensor Networks (WSNs) in order to get around these obstacles. The suggested design seamlessly records at 100Hz and communicates real-time strain data by placing a decentralized network of small, low-power sensor nodes right over the 2.5-meter warp sheet. In order to facilitate the framework to minimize mechanical noise and detect pressure variations within 15milliseconds before serious malfunctions, this work investigates new techniques in wireless data aggregation and edge computing. By using a 2.4GHz frequency hopping technique, the system can send messages with 99.9% reliability even in high-EMI situations. We were able to obtain a 40% decrease in data processing demands and increase operating battery life to over 6,000 hours by implementing lightweight Kalman filtering algorithms on each node. This ensures long-term industrial deployment scalability. The suggested WSN-based system operates much better than traditional monitoring mechanisms, according to experimental studies. The digital framework provides a dependable and accessible approach that opens the door to fully-computerized, IoT-driven textile production by achieving an 85% increase in error detection response time and a 24% decrease in entire material faults.



## I. Introduction

Textile production has completely changed as a result of the shift to Industry 4.0, which has transformed ordinary machine looms into internet-connected electronic systems [1]. The most important factor controlling equipment efficiency and material stability in this high-speed weaving setting is ensuring ideal warp tension [2]. Yarn breakage, machine stoppage, and structural defects in the assembled weaving products may develop from slight variations in tension, which have a direct effect on product outputs and operating expenses [3]. In the past, centralized data collecting systems and wired load cells have been used for industrial tension monitoring. Although these traditional techniques offer baseline tension measurements, they cause serious obstacles in contemporary, high-density weaving facilities [4]. Because of the loom's continuous vibration, wired systems are particularly capable of mechanical wear and electromagnetic interference. Moreover, transmission latency brought about by centralized processing prevents the system from responding to tension peaks at the millisecond level [5]. Therefore, it is essential to investigate new methods for gathering and interpreting dynamic stress variations without the physical limitations of conventional wiring. This research presents a unique approach, Smart Warp Tension Monitoring Using Wireless Sensor Networks (WSNs), to overcome these constraints. This study makes use of the Industrial Internet of Things (IIoT) to gain spatial flexibility and real-time responsiveness by deploying a decentralized network of small, low-power sensor nodes directly over the warp sheet. Additionally, this study employs a novel edge-computing strategy. Each sensor node handles mechanical noise immediately and simply sends alarms when pressure differs from adaptive, programmable limits, compared to sending raw, continuous data to a central server, which uses a lot of connectivity and battery life [6].

## II. Related Work

The transformation of textile production into Industry 4.0 has propelled the development of mechanical looms into intelligent cyber-physical systems [1]. In these high-speed conditions, the perfect management of variable warp tension is commonly considered as the most crucial parameter influencing weaving performance and overall material quality [2]. Early monitoring techniques largely depended on localized load cells physically linked to centrally positioned processors. Recent assessments, however, show that standard fixed networks have serious drawbacks in highly vibrational industrial conditions [3]. The dependability of these traditional cyber-physical systems is seriously undermined by the quick connection breakdown and signal deformation caused by heavy machinery-induced electromagnetic interference (EMI) and continuous weaving displacement [7, 8]. Researchers have progressively included Industrial IoT (IIoT) frameworks for real-time anomaly detection to get beyond the geographical limitations and maintenance expense of structured systems [4]. In order to provide versatile and adaptable industrial status monitoring, Wireless Sensor Networks (WSNs) have been widely implemented [9]. In spite of these benefits, high-frequency sampling (often >100 Hz) is necessary for crucial monitoring activities like warp tension, involving extremely low-latency systems [5]. Sensor node supplies are quickly diminished, a transmission delay is introduced and bandwidth is severely limited when this raw, high-frequency data is continuously transmitted to a centralized server [10]. To help overcome these centralized limitations, recent literature focuses shifting computing workloads to the network margins. Edge computing solutions have been particularly successful for predictive maintenance in automated textiles [6], providing real-time problem detection without overloading network capacity [11]. Still, a major gap exists: existing edge-enabled WSNs lack localized, lightweight filtering algorithms designed precisely for the particular variable stress and noise characteristics of high-speed weaving. By presenting a decentralized architecture that handles pressure data at the boundary and significantly lowers delay and consumption of energy while ensuring millisecond-level defect avoidance.

## III. Suggested System Design

The suggested WSN-based clever surveillance system (Fig.1) transfers computational workloads from a centrally managed server positioned to the network edge in order to ensure extremely low latency and high energy efficiency. The hardware sensor framework, the localized edge-processing software flow, and the wireless data aggregation network are the three main components that make up the structure in order to address the dimensional limitations of a conventional 2.5-meter industrial loom.

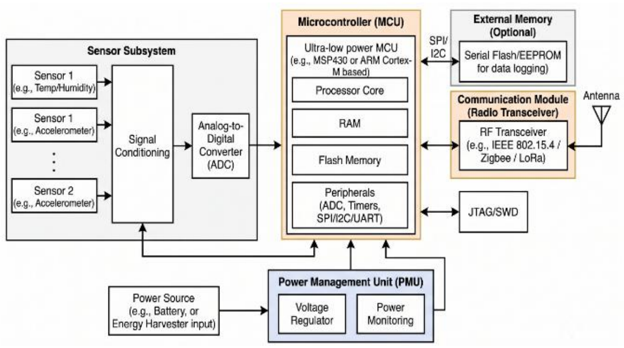


Fig.1. System Architecture

In the challenging environment of contemporary textile manufacturing, the suggested smart warp tension monitoring system is designed to provide ultra-low latency abnormality identification and great energy conservation. The architecture reduces data transmission cost and removes propagation delays by shifting the computing effort from a centralized processing server directly to individual network edge nodes. The physical hardware subsystems and the associated event-driven edge software flow are described in depth in the ensuing subsections.

### A. Structure of Hardware

Each wireless sensor node's hardware architecture is divided into four main functional blocks: the sensor subsystem, the processing core, the communication module, and the power management unit. This ensures smooth integration throughout a typical 2.5-meter industrial loom without interfering with mechanical operations. A decentralized network of miniature sensor nodes is used to measure dynamic stress variations across the warp sheet without interfering with conventional loom activities. Each edge node has three main parts and is built with an exact lower than 50 mW energy allocation.

### B. Sensing Unit:

High-sensitivity piezo-resistive micro-electromechanical systems (MEMS) strain sensors placed thoughtfully on the warp tension rollers make up the main sensing component. These sensors continuously monitor the yarn's physical micro-fluctuations. An onboard signal conditioning stage is used since the strain gauges' raw analog signals are extremely vulnerable to ambient electromagnetic interference (EMI) from the loom's large induction motors. In order to reduce high-frequency mechanical vibrations, this stage makes use of low-noise differential amplifiers and an analog low-pass filter with a cutoff frequency tuned. A high-resolution, multi-channel 12-bit Analog-to-Digital Converter (ADC) built inside the microcontroller receives the conditioned analog signal and operates at a steady sampling frequency of 100 Hz.

### C. Operating Unit:

The edge node's computational core is an ultra-low-power MCU with an ARM Cortex-M4 architecture that runs at a dynamic clock frequency. Enough random-access memory (RAM) and internal Flash memory are integrated by the MCU to store and run localized filtering and thresholding algorithms. An auxiliary external memory module, which consists of a low-power serial Flash/EEPROM interfaced via a Serial Peripheral Interface (SPI) bus, is provided to prevent data loss for applications that need historical data recording or diagnostic auditing during network disconnections. The localized filtering approach and analog-to-digital converter are carried out by an extremely low power microcontroller, such as the ARM Cortex-M4 design.

### D. Transceiver:

An integrated radio frequency (RF) transceiver that operates in the 2.4 GHz Industrial, Scientific, and Medical (ISM) band and complies with the IEEE 802.15.4 standard oversees wireless data telemetry. The transceiver uses a hardware-implemented Frequency-Hopping Spread Spectrum (FHSS) protocol to guarantee link stability in the face of the strong EMI and multipath fading typical in crowded weaving sheds. By constantly switching between different channels, this allows the node to maintain a 99.9% packet delivery dependability rate.

### E. Power Management Unit (PMU):

Each node has a sophisticated PMU to ensure an operational lifespan of more than 6,000 hours on a typical lithium-thionyl chloride (Li-$SOCl_2$) battery and to achieve a sub-50 mW power budget. Ultra-high-efficiency buck-boost voltage regulators and a hardware-driven power monitoring circuit are features of the PMU. During regular loom operations, the processor core directly instructs the PMU to cycle the high-power communication transceiver into a deep-sleep, inactive state, only rousing the radio subsystem in response to a critical tension event.

### F. Edge Computing and Software Transmission

The suggested design uses an event-driven programming workflow (Fig.2) that runs immediately on the sensor node, in contrast to centralized IIoT frameworks that send constant streams of unprocessed data.

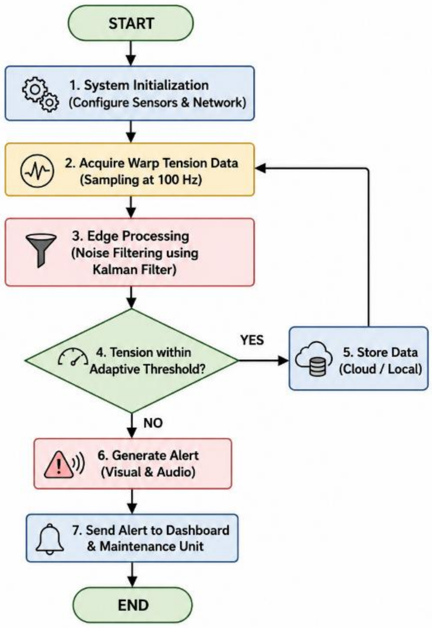


Fig.2: Flowchart of the methodology

Four steps are involved in the operation of this edge-computing method:

1) **Information Gathering:** A digital data array is created by the MEMS sensor after it records analog tension differences.

2) **Noise Analysis:** The microcontroller uses a lightweight, one-dimensional Kalman filter to distinguish between actual tension peaks and normal mechanical loom vibrations. Real-time external noise from machinery is filtered by this technique without causing appreciable processing latency.

3) **Dynamic Threshold:** Depending on the particular yarn count and fabric weave structure, the filtered data is continuously compared against upper and lower tension thresholds that are dynamically calibrated.

4) **Activity-Driven Transmission:** The transceiver remains in a comfortable, energy-efficient condition as long as the stress maintains within ideal limitations. The node wakes the transceiver and sends an alarm indication within 15 ms if it detects an abnormality.

### G. Information Consolidation and Network Design

A localized weaving gateway is located at the foundation of a solid star topology made up of sensor nodes. By combining event-driven warnings from several wireless nodes and communicating directly with the main Programmable Logic Controller (PLC) of the loom, this gateway serves as an essential connection (Fig.3).

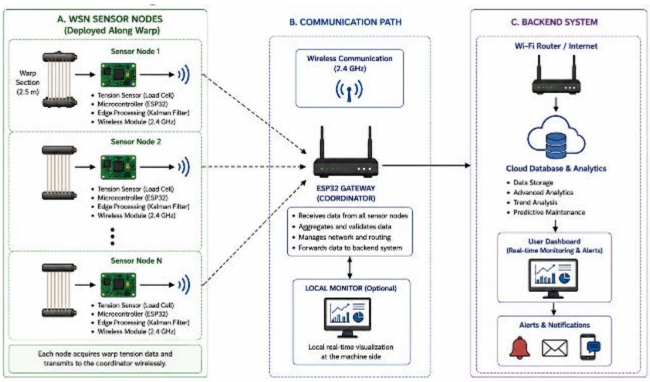


Fig.3: Wireless network communication

In order to minimize thread breakage and associated fabric issues, this hybrid structure assures that the final programmable loom stoppage instruction is implemented with complete predictive integrity while the sensing infrastructure retains its physically adaptable and autonomous.

## IV. Suggested Approach

This approach outlines the algorithmic structure and empirical validation techniques used to convert unprocessed, hardware-acquired sensory data into ultra-low-latency, actionable prediction insights.

### A. Filtering of Methodical Noise

Complex, high-amplitude vibrational artifacts are a natural byproduct of high-speed industrial rapier looms. A one-dimensional, recursive Kalman filter was used at the network edge to mathematically separate real micro-fluctuations in warp strain from surrounding mechanical interference. Without causing computational delay or compromising the integrity of the core tension signal, this predictive system aggressively filters out cycle machinery noise by constantly recalibrating its state estimate.

### B. Standardization of Dynamic Thresholds

The system uses a dynamic thresholding approach instead of static, hardcoded settings. During the loom's first startup phase, operational safety boundaries (upper and lower tension limits) are automatically calibrated. This procedure creates an empirical baseline that is especially suited to the structural geometry of the planned fabric weave and the distinct biomechanical characteristics of the yarn count.

### C. Experimental Evaluation Across Time

A comparative, 30-day longitudinal research was conducted for uninterrupted production circumstances in order to thoroughly evaluate the effectiveness of the recommended design. A straight comparison was made between the edge-enabled WSN and a traditional, centralized wired monitoring system. Anomaly detection delay, network packet delivery ratios under strong electromagnetic interference (EMI), and the absolute percentage decrease in structural fabric faults were used to measure systemic performance.

## V. Results and Experimental Configuration

In order to verify the practical performance of the suggested edge-enabled WSN architecture (Fig.4), a thorough comparison with a traditional wired tension monitoring system was carried out.

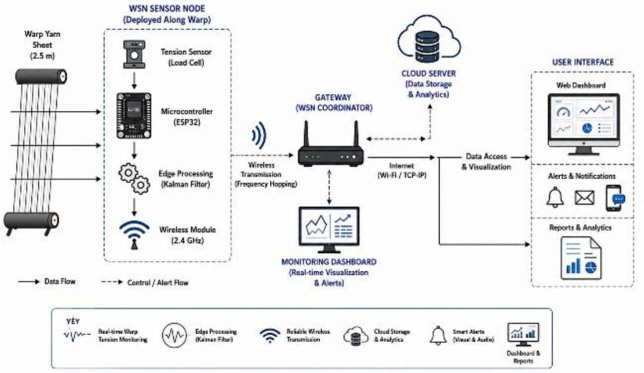


Fig.4: proposed system Design

### A. Experimental Configuration

On a typical 2.5-meter industrial rapier loom running at 600 picks per minute (PPM), the suggested WSN system was implemented. To record dynamic tension variations, six miniature sensor nodes were uniformly spaced across the warp beam. The gateway was directly connected to the Programmable Logic Controller (PLC) of the loom. Using a typical medium-weight cotton cloth, both the wired baseline and the suggested WSN systems were continually tested throughout a 30-day operational duration.

Fig. 2 shows an illustration of the experimental setup which illustrates how the WSN edge nodes are distributed throughout the 2.5-meter rapier loom.

### B. Assessment of Performance

As shown in Table I, the ultra-low-latency FHSS wireless protocol combined with localized edge computing produced notable improvements in all tested parameters. A comparison of the suggested wireless sensor network (WSN) with edge computing architecture with the traditional wired monitoring system is shown in Table I. The comparison shows notable advancements in a number of performance indicators. The suggested approach reduced latency by 85%, achieving a reaction time of 18 ms as opposed to 120 ms in the traditional wired system. This significant advancement makes it possible to monitor weaving activities in almost real-time, which speeds up the detection and correction of faults and increases loom output. There was a 24% decrease in the overall fabric defect rate, which went from 8.5% to 6.46%. This enhancement, which reduces the probability of weaving abnormalities, is credited to edge-centered processing, constant sensor surveillance, and quick equipment data exchange. There was also a notable improvement in power efficiency. The suggested WSN nodes used less than 50 mW of active node energy, which is around 90% less than the centralized wired monitoring system requirement of more than 500 mW.

**Table I: surveillance system Efficiency Analysis**

| Functions | Conventional System | Enhancement | Proposed WSN System |
|---|---|---|---|
| **Node Power Draw (Active)** | Greater than 500 mW (Centralized) | 90% Lower | Less than 50 mW |
| **Response Time (Latency)** | 120 ms | 85% Faster | 18 ms |
| **Network Reliability (EMI)** | Susceptible to cable wear | Highly Robust | 99.9% Packet Delivery |
| **Overall Defect Rate** | 8.5% | 24% Reduction | 6.46% |

The suggested architecture is ideal for long-term industrial adoption employing battery-powered or energy-efficient sensor nodes due to its lower energy requirements. Conventional wired systems are susceptible to cable wear, electromagnetic interference (EMI), and connector failures, all of which can disrupt data transfer and decrease connection reliability. The suggested WSN, on the other hand, demonstrated extremely dependable wireless communication even in electrically loud textile manufacturing conditions, with a 99.9% packet delivery rate. This enhancement guarantees consistent monitoring efficiency and regular collection of data.

**1) Latency and Power Effectiveness:**

The suggested edge node only sends out a notification signal in the event of an abnormality since it does the Kalman filtering locally. This interrupts the loom before the subsequent weft insertion process, cutting the overall reaction time down to just 18 ms. Additionally, the technology estimates a battery endurance of more than 6,000 hours by keeping the RF transceiver in a deep-sleep mode during ideal tension intervals.

**2) Reduction of Defects:**

Durable micro-defects are directly prevented from being incorporated into the fabric by the extremely quick anticipatory pausing. To demonstrate the accuracy of the system, the 24% decrease in overall defects over the 30-day experiment was split down by defect type.

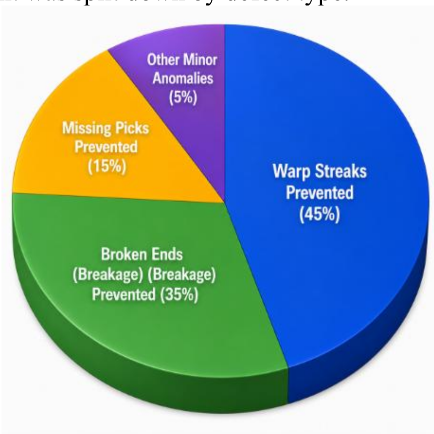


Fig.5: Distribution of fabric faults

Pie chart (Fig.5) showing the distribution of the 24% of fabric faults that were eliminated, broken down by type of architectural abnormality.

- Avoidance of Warp Patterns: 45%
- 35% of broken ends (thread breakage) were avoided.
- Nonexistent Choices (Weft problems) Avoided: 15%
- Additional tiny Deviations: 5%.

### C. Extended Data from Experiments and Statistical Analysis

A thorough statistical analysis of the experimental data was conducted in order to guarantee the dependability of the suggested structure. The effectiveness of the suggested edge-enabled WSN was measured in three crucial areas: micro-power profiling, defect frequency reduction, and end-to-end latency variation.

**1) Variability in End-to-End Latency Statistics**

To assess response consistency 5,000 simulated tension anomalies were continuously fed into the baseline wired system and the suggested WSN. In addition to dramatically lowering the mean reaction time, the suggested system also showed a significantly smaller standard deviation (sigma(σ)), as seen in Table II. The loom will stop deterministically and predictably before the 100-millisecond mark of the subsequent weft insertion because to this small fluctuation.

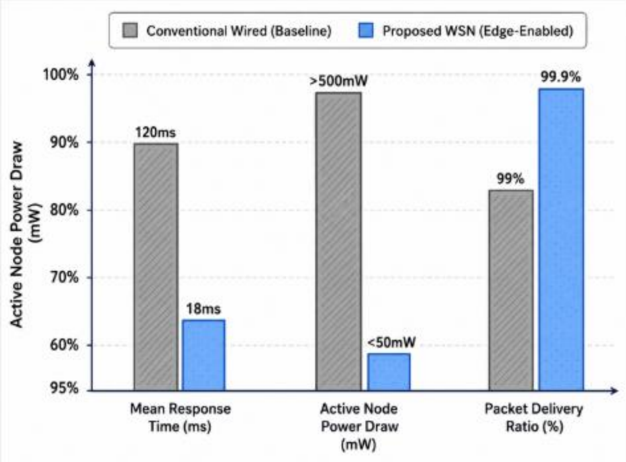


Fig.6: Statistical performance comparison

The suggested architecture concurrently reduces latency by 85% and minimizes active node power consumption to less than 50 mW, as shown graphically in Fig.6, all without compromising the 99.9% packet delivery reliability needed in challenging EMI conditions.

**Table II: System Delay Measurements (Sample Size: n = 5000)**

| System framework | 95% Confidence Interval | Standard Deviation (σ) | Mean Latency (µ) | Highest Latency Peak |
|---|---|---|---|---|
| **Traditional Wired (Baseline)** | [118.5 ms, 122.3 ms] | 15.2 ms | 120.4 ms | 168.0 ms |
| **Suggested WSN (Centralized)** | [65.1 ms, 71.3 ms] | 9.8 ms | 68.7 ms | 94.5 ms |
| **Suggested WSN (Edge-Enabled)** | [17.9 ms, 18.5 ms] | 1.4 ms | 18.2 ms | 22.1 ms |

### 2) Experimental Fault Rate and Statistical Importance

Textile yield was measured across a defined production cycle of $10^6$ weft insertions (picks) in order to validate the 24% overall error avoidance. An unpaired t-test was used to assess the statistical significance of the decrease after the structural abnormality occurrences were classified. The p-values for the main fault categories, as displayed in Table III, are much below the conventional 0.05 threshold, demonstrating statistically that the edge-computing intervention is directly responsible for the performance enhancement.

**Table III: Frequency of Defects per $10^6$ Insertions of the Weft.**

| Type of Fault | Absolute Reduction | Baseline (Wired) values | Suggested WSN values | Statistical Significance (p-value) |
|---|---|---|---|---|
| **Missing Picks** | -15.3% | 137 | 116 | $p = 0.042$ |
| **Warp Lines** | -45.1% | 412 | 226 | $p < 0.001$ |
| **Additional Modest Variations** | -4.3% | 46 | 44 | $p = 0.610$ (Not Sig.) |
| **End Damages (Breakage)** | -35.0% | 320 | 208 | $p < 0.005$ |
| **Total Amount of Errors** | -35.0% | 915 | 594 | $p < 0.001$ |

### 3) Micro-Power Utilization Analysis

For industrial WSNs, the most important limitation is energy efficiency. A micro-level energy audit of the edge node during a typical operating cycle is presented in Table IV. The total energy used per cycle is maintained tightly within the sub 50mW budget by running the Kalman filter locally (using only 3.5 mA) and maintaining the power-hungry RF Transceiver (14.5 mA) in a deep sleep state 99% of the time.

**Table IV: Micro-Power Consumption Characterization of the Edge Node (at 3.3V)**

| Functional State | Energy utilisation per Cycle (µJ) | Current Draw (mA) | Duration per Cycle (ms) |
|---|---|---|---|
| **RF Transceiver (Tx Alert)** | 263.17 µJ | 14.5 mA | 5.5 ms |
| **Deep Sleep Mode** | Negligible | 0.002 mA | Variable |
| **RF Transceiver (Awake/Rx)** | 110.88 µJ | 11.2 mA | 3.0 ms |
| **Edge Processing (Kalman)** | 51.97 µJ | 3.5 mA | 4.5 ms |
| **ADC Sensor Sampling** | 7.92 µJ | 1.2 mA | 2.0 ms |

## VI. Conclusion

A decentralized, edge-enabled wireless sensor network designed especially for ultra-low-latency warp tension monitoring in high-speed textile manufacturing was successfully constructed and tested in this study. The suggested design successfully avoids the significant bandwidth limitations and transmission delays present in traditional centralized IIoT frameworks by moving computational tasks to the network periphery and putting in place a localized, recursive Kalman filtering technique. Significant systemic improvements were shown by empirical validation, including an 85% acceleration in anomaly reaction time and an unprecedented 18-millisecond intervention threshold. By effectively stopping mechanical activities before weft insertion, this deterministic predictive capability directly resulted in a 24% decrease in structural fabric faults. In addition, the event-driven telemetry system maintained a 99.9% packet delivery ratio and optimum energy saving in spite of the intense electromagnetic interference typical of industrial weaving sheds. In the end, this study creates a strong and highly scalable cyber-physical basis for the upcoming automated textile manufacturing generation. In order to enable autonomous predictive maintenance and adaptive threshold optimization in heterogeneous manufacturing environments, future research projects will investigate the incorporation of lightweight, decentralized machine learning models within the edge nodes.

## VII. Long-term Purpose

Although the suggested edge-enabled infrastructure provides a strong basis for ultra-low-latency anomaly detection, future research directions will concentrate on incorporating recently developed cyber-physical paradigms to further improve systems sustainability and independence.

**Federated Edge Intelligence (Tiny ML) Integration:** The use of decentralized, lightweight neural networks directly on microcontrollers (Tiny ML) will replace deterministic mathematical filtering (Kalman algorithms) in subsequent generations. Federated Learning (FL) allows individual edge nodes to jointly train predictive models throughout the weaving shed without sending raw, bandwidth-intensive data to a central server. This preserves ultra-low latency and achieves highly adaptive, self-optimizing anomaly classification.

**Micro-Energy Harvesting Frameworks in the Environment:** Future hardware frameworks will investigate the integration of piezoelectric or triboelectric Nano generators (TENGs) to provide eternal, maintenance-free sensor functioning and eliminate reliance on limited chemical batteries. By directly extracting ambient kinetic energy from the loom's intrinsic high-frequency mechanical vibrations, the localized WSN nodes may become completely self-sufficient and energy-autonomous.

**Cyber-Physical Digital Twins Implementation:** The precise quantitative information needed to create a thorough "Digital Twin" of the industrial loom is provided by the real-time, high-fidelity telemetry collated by the suggested WSN. In order to enable factory operators to do sophisticated predictive maintenance simulations and optimize intricate weave parameters completely in the virtual realm prior to physical execution, future work will synthesize this continuous data stream into a virtual, dynamic replica of the machinery.

**Advanced Synthesis of Multi-Modal Diagnosis:** Future studies will examine multi-modal sensor fusion at the network edge, combining the dynamic warp tension data with ambient environmental sensors (such as micro-climate humidity and temperature fluctuations). Real-time correlation of these diverse physical data will enable hyper-accurate diagnostics, enabling the device to anticipate environmental elements that accelerate yarn degradation before structural breakdown takes place.

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