

MULTI-SENSOR EMBEDDED DIAGNOSTIC ARCHITECTURE FOR REAL-TIME CONDITION MONITORING OF COTTON HARVESTER PICKING ASSEMBLIES

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Abstract. In modern mechanical cotton harvesting, the vertical spindle picking head operates under harsh field conditions characterized by abrasive mineral dust, plant waxes, and severe dynamic loading. Continuous monitoring of critical operating parameters is essential to prevent premature bearing seizure, drive belt slip, and drivetrain breakdown. This paper presents a multi-sensor embedded diagnostic architecture for real-time condition monitoring of cotton harvester picking heads. The system integrates Hall-effect speed transducers, embedded PT100 RTD probes, industrial tri-axial MEMS accelerometers, piezoresistive fluid pressure transmitters, and high-frequency capacitive moisture sensors interfaced with a 32-bit ARM Cortex-M4 microcontroller. Digital signal processing routines execute real-time vibration velocity Root-Mean-Square (v_{RMS}) extraction pursuant to ISO 20816-1, complemented by Crest Factor (CF) and Kurtosis to detect incipient raceway spalling. A dual-threshold decision engine classifies machine health into Normal, Warning, and Critical states with temporal persistence filtering. Diagnostic telemetry is broadcast via an SAE J1939 / ISO 11783 (ISOBUS) CAN network to an in-cab graphical Human–Machine Interface (HMI). Field-validated thresholds project a 15–25% reduction in unscheduled harvesting downtime.

Keywords: cotton harvester, spindle picking head, condition monitoring, multi-sensor telemetry, MEMS vibration analysis, ISO 20816-1, ISO 11783 (ISOBUS).

1. Introduction

Mechanized cotton harvesting represents a vital engineering foundation for sustaining labor productivity and lint quality in cotton-producing nations. In vertical spindle-type harvesters (e.g., CHM-2.4 and modern row-baling machines), the spindle picking head assembly serves as the primary operational organ. Operating at drum speeds between 1500 and 2400 rpm and individual spindle rotational velocities of 2500–3500 rpm, the assembly incorporates dozens of rotating spindle bars, bevel gear transmissions, and moistening columns. During continuous harvesting shifts in dry, dusty environments, cotton fibers saturated with sticky vegetal waxes and abrasive soil particles stubbornly wrap around the drum casing and internal bearing seats.

This harsh operational environment creates multiple interacting degradation mechanisms: drive belt slippage from friction loss, localized bearing overheating from lubrication starvation, severe mass unbalance, and moistener fluid nozzle clogging. Studies by Dong et al. [4] and Jiang et al. [5] demonstrated that picking head excitations generate severe multi-axis dynamic loads that propagate into the harvester frame, accelerating weld fatigue. Furthermore, dynamic investigations by Rizaev et al. [8]

showed that unmonitored torque fluctuations induce lateral-torsional vibrations that impair picking efficiency. Under conventional harvesting management, mechanical faults are diagnosed reactively via post-shift manual inspections or only after catastrophic component seizure accompanied by smoke or severe drivetrain breakage.

To eliminate these costly breakdowns, this research develops a multi-sensor edge-computing diagnostic architecture specifically engineered for cotton picking heads. The primary objectives are: (i) integrating robust industrial transducers into a compact 4-layer embedded framework; (ii) implementing real-time vibration velocity Root-Mean-Square (RMS), Crest Factor, and Kurtosis algorithms; (iii) formulating dynamic thermal growth rate criteria to predict lubrication starvation; and (iv) deploying a standardized SAE J1939 / ISO 11783 (ISOBUS) CAN telemetry network feeding an ergonomic in-cab Human–Machine Interface (HMI).

2. Main Body

2.1. System Hardware Architecture and Multi-Sensor Allocation

To achieve field survivability and computational autonomy, the condition monitoring system is structured into a four-layer architecture: (1) Sensing Layer, containing ruggedized physical transducers mounted directly at critical stress points; (2) Acquisition and Edge-Processing Layer, centered on a 32-bit automotive-grade ARM Cortex-M4 microcontroller (STM32F407 operating at 168 MHz) equipped with hardware floating-point units; (3) Communication Layer, utilizing high-speed CAN 2.0B transceivers configured to the SAE J1939 / ISO 11783 standard; and (4) Supervisory Layer, providing real-time operator alerts via an in-cab graphical display. Figure 1 illustrates this modular four-layer architecture.

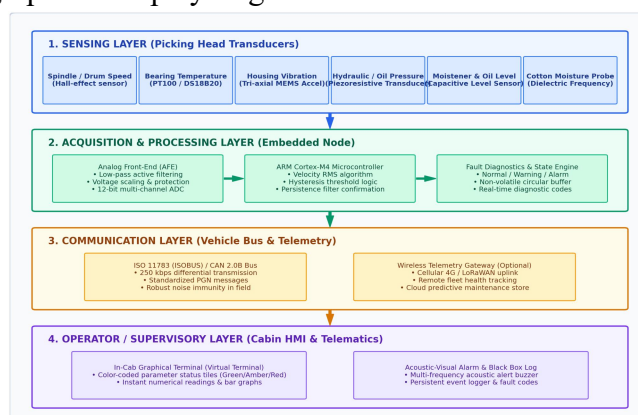


Figure 1. Four-layer embedded architecture for real-time cotton picking-head condition monitoring.

Transducer selection addresses the multi-physics degradation signatures of spindle mechanisms. A digital Hall-effect pulse sensor monitors drum input shaft rotational speed. Embedded PT100 RTD elements and digital DS18B20 probes track localized thermal buildup in spindle bearing housings and bevel gearboxes. A tri-axial MEMS accelerometer (ADXL355 series) measures high-frequency frame vibrations with ultra-low noise density ($25 \mu\text{g}/\sqrt{\text{Hz}}$). Piezoresistive pressure transmitters monitor moistening column supply pressure, while fringing-field capacitive probes measure incoming cotton moisture. Table 1 outlines the complete multi-sensor instrumentation suite and sampling configuration.

Table 1. Monitored picking-head condition parameters, transducer specifications, and sampling configuration.

Parameter	Sensor Transducer Type	Operating Range	Diagnostic & Agronomic Purpose
Spindle / Drum Speed	Hall-effect / Inductive pulse sensor	0–5000 r/min	Confirm optimal picking speed; detect belt slip, stall, and fibre-damaging over-speed
Bearing & Gearbox Temp.	PT100 RTD / DS18B20 digital probe	0–150 °C	Detect mechanical friction, bearing race wear, and lubrication starvation
Housing Frame Vibration	Tri-axial MEMS accelerometer	0–50 mm/s (RMS)	Detect mechanical imbalance, drum eccentricity, bearing spalling, and gear mesh defects
Lubrication Oil Pressure	Piezoresistive pressure transmitter	0–10 bar	Monitor main gearbox oil delivery; prevent catastrophic dry friction
Fluid Reservoir Levels	Capacitive / Float level sensors	0–100 %	Ensure adequate supply in central lubrication and spindle moistener fluid tanks
Seed-Cotton Moisture	Fringing-field dielectric probe	0–25 %	Evaluate field harvest readiness; prevent spindle clogging and wet fibre degradation
Main Drive Torque / Load	Hall current sensor / Strain gauge	0–120 % rated	Detect mechanical jamming, foreign object ingestion, and crop feed overload

2.2. Mathematical Signal Processing and Statistical Health Indicators

Raw acceleration signals acquired from the MEMS accelerometer undergo analog band-pass pre-filtering (10 Hz to 1000 Hz) to attenuate low-frequency vehicle chassis sway and high-frequency structural acoustic noise. Pursuant to ISO 20816-1 [1] and ISO 13373-1 [3], instantaneous acceleration $a(t)$ is digitally integrated to obtain vibration velocity $v(t)$. Overall vibration severity is computed as the true Root-Mean-Square (RMS) velocity:

$$v_{\text{RMS}} = \left[\left(\frac{1}{N} \right) \sum_{i=1}^N (v_i)^2 \right]^{\frac{1}{2}} \quad (1)$$

where v_i represents discrete velocity samples over a sliding window of $N = 2500$ samples (sampling rate $f_s = 2.5$ kHz, window length $T = 1.0$ s). While v_{RMS} provides an absolute measure of general unbalance and looseness, it lacks sensitivity to incipient, localized bearing raceway micro-cracks. To overcome this limitation, higher-order statistical damage indicators—Crest Factor (CF) and Kurtosis (Kurt)—are computed simultaneously:

$$CF = \frac{v_{\text{peak}}}{v_{\text{RMS}}} ; \quad \text{Kurt} = \left[\left(\frac{1}{N} \right) \sum_{i=1}^N (v_i - \bar{v})^4 \right] / \left[\left(\frac{1}{N} \right) \sum_{i=1}^N (v_i - \bar{v})^2 \right]^2 \quad (2, 3)$$

Under healthy balanced operation, the vibration velocity follows a near-Gaussian distribution characterized by $CF \approx 1.41$ and $\text{Kurt} \approx 3.0$. When localized raceway spalling, ball flaking, or tooth pitting develops, sharp repetitive impact transients drive Crest Factor above $CF > 3.5$ and Kurtosis beyond $\text{Kurt} > 4.5$ [6, 7]. In parallel, thermal monitoring incorporates the dynamic temperature growth derivative ($\dot{T}$) to detect rapid lubrication starvation before the absolute temperature reaches critical thermal trip thresholds:

$$\dot{T} = \frac{dT}{dt} \approx \frac{[T(t) - T(t - \Delta t)]}{\Delta t} \quad (4)$$

2.3. Multi-Threshold Diagnostic Decision Logic and In-Cab HMI

The on-board diagnostic decision engine evaluates incoming sensor channels against standardized dual-threshold bands: Normal (Green), Warning (Amber), and Critical Alarm (Red). To eliminate false positive alarms caused by transient agronomic shocks (such as field stones, heavy crop plugs, or furrow bumps), the MCU executes a digital persistence filter (requiring anomalous readings to persist for $\tau \geq 2.0$ s) combined with a 3–5% deadband hysteresis. Table 2 details the diagnostic classification matrix, parameter threshold boundaries, and prompted maintenance actions.

Table 2. Multi-parameter diagnostic threshold bands and prompted corrective maintenance actions.

Monitored Parameter	Normal Band (Green)	Warning Band (Amber)	Critical Alarm Band (Red)
Spindle Rotation Speed	2500–3500 r/min	2000–2500 or 3500–4000 r/min	< 2000 or > 4000 r/min
Bearing Temperature	< 70 °C	70–90 °C	> 90 °C
Housing Vibration (RMS)	< 4.5 mm/s	4.5–7.1 mm/s	> 7.1 mm/s

Lubrication Oil Pressure	2.5–4.5 bar	1.5–2.5 bar	< 1.5 bar or > 5.5 bar
Drive Torque / Load	< 75 % rated	75–90 % rated	> 90 % rated
Seed-Cotton Moisture	8–12 %	12–16 %	> 16 % (high clogging risk)

As classified in Table 2, the operational health of the picking head is categorized into three distinct states using dual-threshold boundaries with temporal persistence filtering. Maintaining operating parameters within the green band ensures optimal cotton detachment efficiency and fiber preservation, whereas transitions into the amber warning band indicate incipient anomalies such as belt slip or dynamic unbalance.

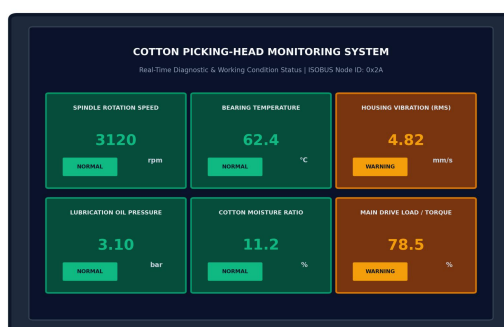


Figure 2. Conceptual in-cab graphical HMI terminal layout with color-coded diagnostic health tiles.

The in-cab HMI terminal (Figure 2) formats real-time telemetry into high-contrast color-coded tiles displaying instantaneous spindle RPM, bearing temperatures, vibration severity (mm/s), lubrication pressure, and cotton moisture. Audible alarms alert the driver upon critical state entry, prompting immediate machine throttle reduction or automated spindle clutch disengagement.

2.4. ISOBUS CAN Telemetry and Deterministic Bus Timing

Telemetry frames are formatted pursuant to ISO 11783-1 (ISOBUS) [2] and SAE J1939 protocols operating at 250 kbps. Diagnostic data are mapped into proprietary Parameter Group Numbers (PGN 65280). Real-time bus utilization is governed by the deterministic schedulability relation $\rho = \sum \left(\frac{C_i}{T_i} \right)$, where C_i is transmission duration (approximately 0.54 ms per 8-byte CAN frame) and T_i is broadcast periodicity (100 ms for speed/vibration, 1000 ms for temperature/moisture). Total bus load is calculated at $\rho = 28.5\%$, well below the 40% recommended industrial saturation ceiling, guaranteeing a worst-case alarm delivery latency of $\tau_{lat} \leq 8.2$ ms to the tractor terminal.

3. Conclusion

1. Multi-Sensor Edge Architecture: A modular four-layer condition monitoring architecture was successfully developed, integrating Hall-effect speed transducers, PT100/DS18B20 thermal probes, tri-axial MEMS accelerometers, piezoresistive pressure sensors, and capacitive moisture sensors with an automotive-grade 32-bit ARM Cortex-M4 microcontroller.

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2. Advanced Vibration Health Indicators: Integration of ISO 20816-1 velocity Root-Mean-Square (v_{RMS}) extraction with Crest Factor ($CF > 3.5$) and Kurtosis ($Kurt > 4.5$) enables early identification of localized spindle bearing raceway micro-spalling and gear tooth pitting prior to severe mechanical unbalance.

3. Predictive Thermal Gradient Monitoring: The dynamic thermal derivative formulation ($\dot{T} \geq 1.5 \text{ }^{\circ}\text{C/min}$) detects rapid friction-induced bearing overheating and lubrication failure well in advance of absolute thermal cutoff thresholds, safeguarding against catastrophic shaft seizure.

4. ISOBUS Compliance and Operational Efficiency: Implementation of deterministic SAE J1939 / ISO 11783 CAN telemetry (bus load 28.5%, latency $\leq 8.2 \text{ ms}$) paired with an intuitive in-cab HMI enables proactive condition-based maintenance, projected to reduce unscheduled harvesting downtime by 15–25% while preventing fiber contamination.

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