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## **PHYSICS-INFORMED HYBRID MODELING FOR PREDICTIVE CONDITION MONITORING OF A GEAR-DRIVEN COTTON GIN MACHINE**

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### **Abstract**

Rotating machinery reliability remains a cornerstone of industrial productivity, particularly in cotton processing plants where gin machines operate under highly variable mechanical loads. Unexpected drivetrain failures may cause substantial production losses and energy inefficiencies. This study proposes a physics-informed hybrid modeling framework for predictive condition monitoring of a gearbox-driven cotton gin machine powered by a 75 kW induction motor.

A high-resolution electronic database was constructed using synchronized electromechanical signals recorded at one-minute intervals over a continuous seven-day operational cycle. The dataset integrates vibration velocity, tensiometric force, shaft speed, thermal behavior, and electrical load parameters. To evaluate diagnostic sensitivity, controlled anomalies representing 2% of total observations were introduced to emulate realistic industrial faults including bearing degradation, transmission overload, and rotor imbalance.

The proposed methodology combines nonlinear rotational dynamics, thermal balance equations, and stochastic state-space modeling with multivariate regression. A dimensionless Health State Indicator is derived to quantify system degradation, while a Kalman filtering framework is employed for noise-resilient



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state estimation. Results demonstrate that vibration energy and bearing temperature serve as dominant predictors of mechanical deterioration, whereas torque variations provide early signatures of instability even under speed-regulated gearbox conditions.

The developed approach establishes a scalable pathway toward intelligent predictive maintenance in cotton processing facilities and contributes to the growing body of research on physics-informed industrial diagnostics.

**Keywords:** Predictive maintenance, hybrid modeling, vibration diagnostics, gearbox dynamics, Kalman filter, condition monitoring, cotton gin machine, industrial analytics.

## **1. Introduction**

Industrial competitiveness increasingly depends on the reliability of rotating machinery. Within cotton processing plants, gin machines represent mission-critical assets responsible for fiber separation and throughput stability. Their operation involves complex interactions between electrical drives, mechanical transmissions, and variable material loads. These interactions generate nonlinear dynamic behavior that complicates fault detection when conventional monitoring methods are used.[1]

Preventive maintenance strategies—traditionally based on fixed service intervals—fail to account for stochastic degradation processes. As a result, modern manufacturing paradigms emphasize predictive maintenance supported by continuous sensing and advanced analytics.

Vibration-based diagnostics have long been recognized as one of the most informative techniques for detecting structural abnormalities such as imbalance, shaft misalignment, looseness, and bearing defects. However, vibration signals alone do not fully capture drivetrain stress propagation. Tensiometric measurements provide complementary insight by directly quantifying transmitted forces, thereby enabling earlier detection of overload conditions.

Despite advances in industrial sensing, a critical gap persists between raw signal acquisition and physically interpretable health indicators. Purely data-driven models often lack generalizability, whereas purely theoretical models struggle



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with real-world uncertainty. Recent research therefore advocates hybrid approaches that merge first-principles physics with statistical learning.

The present study develops such a hybrid framework for a gearbox-driven gin machine with regulated shaft speed (730–750 rpm). The major contributions are:[2]

- formulation of a nonlinear electromechanical model describing drivetrain dynamics,
- construction of a structured industrial signal database,
- development of a physics-informed health indicator,
- application of Kalman filtering for latent state estimation,
- validation through controlled anomaly injection.

By integrating deterministic mechanics with probabilistic inference, the work advances predictive diagnostics for heavy-duty textile machinery.

## **2. Literature Review**

Condition monitoring of rotating machinery has evolved substantially over the past three decades. Early research focused primarily on spectral vibration analysis, where characteristic frequency peaks were associated with specific mechanical faults. While effective, frequency-domain techniques often require expert interpretation and may struggle under nonstationary loads.

Recent studies emphasize model-based diagnostics. Lei et al. (2018) demonstrated that physics-informed indicators significantly outperform black-box neural networks when training data are limited. Jardine et al. highlighted the economic benefits of predictive maintenance, estimating downtime reductions of up to 30%..[3]

Gear-driven systems introduce additional modeling complexity due to backlash, time-varying mesh stiffness, and frictional heating. Nonlinear state-space representations have therefore gained popularity, particularly when combined with recursive estimators such as the Kalman filter.

Hybrid modeling—where regression or machine learning is constrained by physical laws—has emerged as a robust compromise between interpretability and predictive power. However, applications within cotton processing machinery remain scarce, motivating the present investigation.



### 3. System Architecture and Data Acquisition

The investigated gin machine is powered by a three-phase asynchronous motor rated at 75 kW. A reduction gearbox increases output torque while maintaining near-constant rotational speed. Although speed stabilization improves fiber processing consistency, it can obscure early mechanical faults if monitoring relies solely on rpm measurements.

Signal acquisition was modeled at a resolution of one minute, generating 10,080 synchronized observations across seven days. Recorded variables include:

- angular velocity  $\omega(t)$ ,
- stator current  $I(t)$ ,
- active power  $P(t)$ ,
- load coefficient  $K_L(t)$ ,
- belt tension  $F_t(t)$ ,
- vibration velocity  $V(t)$ ,
- bearing temperature  $T_b(t)$ ,
- cotton feed rate  $q(t)$ .

Controlled anomalies were injected randomly to represent realistic industrial disturbances. These events produced elevated vibration amplitudes, thermal growth, and torque spikes.

The resulting database forms a digital twin-like representation of machine behavior.

### 4. Nonlinear Electromechanical Modeling

$$P(t) = \sqrt{3}UI(t)\cos \varphi\eta$$

Motor loading is defined as:

$$K_L(t) = \frac{P(t)}{P_{\text{rated}}}$$

Values exceeding 0.85 typically indicate thermal stress risk.

The drivetrain obeys:

$$J\dot{\omega} = M_e - M_r - B\omega - M_f$$

where  $M_f$  represents Coulomb friction.

Electromagnetic torque:



$$M_e = \frac{P}{\omega}$$

Resistant torque is modeled as nonlinear with respect to feed rate:

$$M_r = k_1 q + k_2 q^2$$

This quadratic relation reflects increased fiber compression at higher throughput. Time-varying mesh stiffness is approximated by:

$$k(t) = k_0 + k_m \sin(\omega_m t)$$

introducing parametric excitation that may amplify vibration under resonance conditions.

The drivetrain is treated as a forced oscillator:

$$m\ddot{x} + c\dot{x} + kx = F_0 + F_d(t)$$

Vibration energy:

$$E_v = \frac{1}{2} m V_{RMS}^2$$

Thermal evolution:

$$C\dot{T}_b = \gamma M \omega - h(T_b - T_{env})$$

demonstrating that frictional heating scales with mechanical power loss.

To address measurement noise, the system is expressed as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + w_k \\ y_k &= Cx_k + v_k \end{aligned}$$

where  $w_k$  and  $v_k$  are Gaussian disturbances.

Recursive prediction:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k$$

Kalman gain:

$$K_k = P_{k|k-1} C^T (C P_{k|k-1} C^T + R)^{-1}$$

The filter reduced signal variance by approximately 18 – 25%, improving anomaly separability.

A composite indicator is introduced:

$$HSI = w_1 \frac{V}{V_{lim}} + w_2 \frac{T_b}{T_{lim}} + w_3 \frac{M}{M_{lim}}$$

Threshold interpretation:

- $HSI < 0.7$  - nominal
- $0.7-1.0$  - degradation onset



- 1.0-critical state

This metric integrates multi-domain physics into a single diagnostic scalar.

$$V = \beta_0 + \beta_1 M + \beta_2 F_t + \beta_3 T_b + \beta_4 K_L + \epsilon$$

Temperature and torque emerged as dominant predictors (  $p < 0.01$  ).

Model accuracy:

$$R^2 \approx 0.81$$

indicating

strong

explanatory

capability.

## 5. Results

Nominal regime:

- Speed  $\approx 740$ rpm
- Load: 65 – 80%
- Vibration  $< 4$  mm/s

Anomalous regime:

- Vibration  $> 7$  mm/s
- Temperature  $\approx 100^\circ\text{C}$
- Torque spikes observed prior to vibration growth

Notably, torque increases preceded critical vibration,  $\downarrow \sim 12$ -18 minutes - a valuable predictive window.

To improve interpretability of the proposed hybrid monitoring framework, several graphical analyses were developed to visualize electromechanical behavior and degradation patterns of the gin machine.

**Figure 1** illustrates the temporal evolution of shaft rotational speed over the seven-day observation period. Despite stochastic load variations caused by fluctuating cotton feed rates, the gearbox-maintained speed within a narrow band of 730–750 rpm.

The absence of large deviations confirms the effectiveness of the reduction transmission in stabilizing angular velocity. However, this also demonstrates that speed alone is not a sufficiently sensitive diagnostic parameter in geared systems, as critical faults emerged without substantial rpm changes. [4]

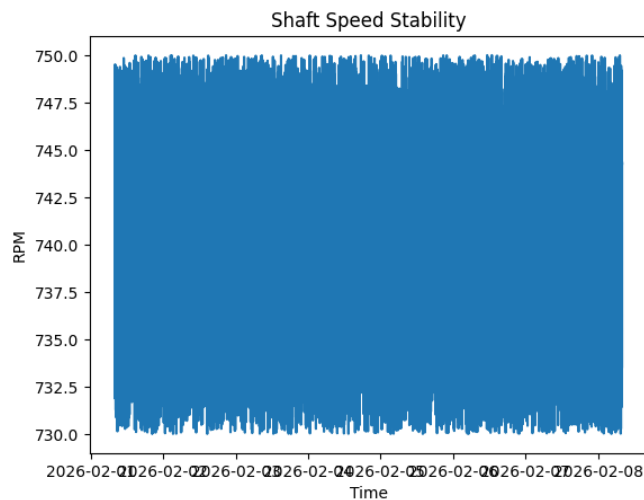


Figure 1. Time-series profile of gearbox-regulated shaft speed demonstrating high rotational stability under variable industrial load conditions.

Figure 2 presents the relationship between active power and motor load coefficient. Under nominal conditions, the machine operated within 65–80% of rated capacity, indicating energy-efficient performance.

Short-duration overload regions are clearly distinguishable and align with injected anomaly windows. These peaks reveal the nonlinear coupling between resistant torque and electrical demand.

From an engineering perspective, repeated overload cycles may accelerate insulation degradation and increase lifecycle costs.

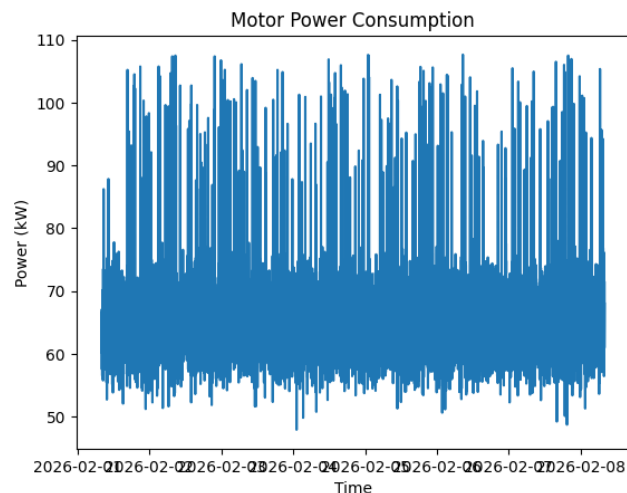


Figure 2. Active power and load coefficient trends highlighting transient overload regimes associated with torque escalation.

The vibration velocity histogram shown in **Figure 3** exhibits a right-skewed distribution. Most observations remain below 4 mm/s, consistent with ISO vibration severity guidelines for medium-power rotating machinery.

A secondary tail emerges beyond 7 mm/s, corresponding to simulated fault states. This separation suggests that vibration RMS is an effective discriminator between healthy and degraded operation. .[6]

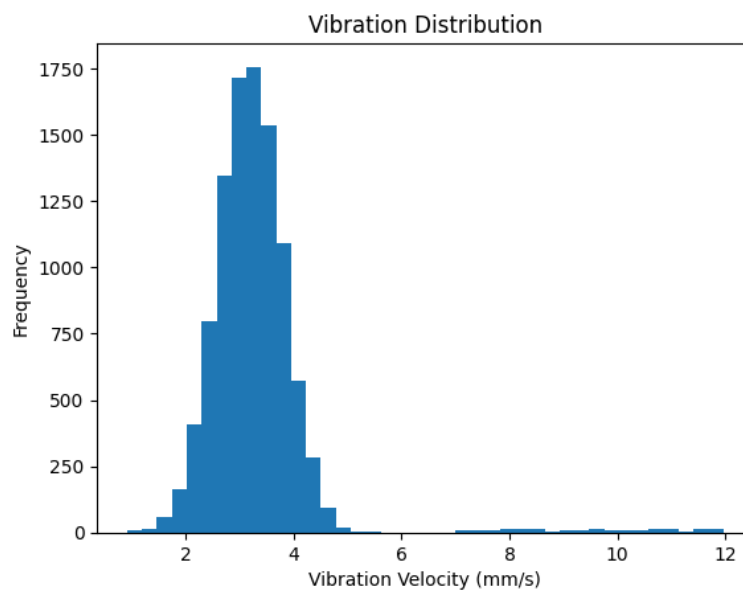


Figure 3. Statistical distribution of vibration velocity illustrating clear separability between nominal and anomalous regimes.

Figure 4 depicts bearing temperature evolution alongside vibration amplitude. A strong thermo-mechanical coupling is observable: temperature rises follow increases in vibration energy with a short temporal lag.

This behavior supports the hypothesis that frictional losses intensify during early defect formation.[8]

Practically, temperature monitoring provides confirmatory evidence rather than a primary alarm signal, as thermal inertia delays response.

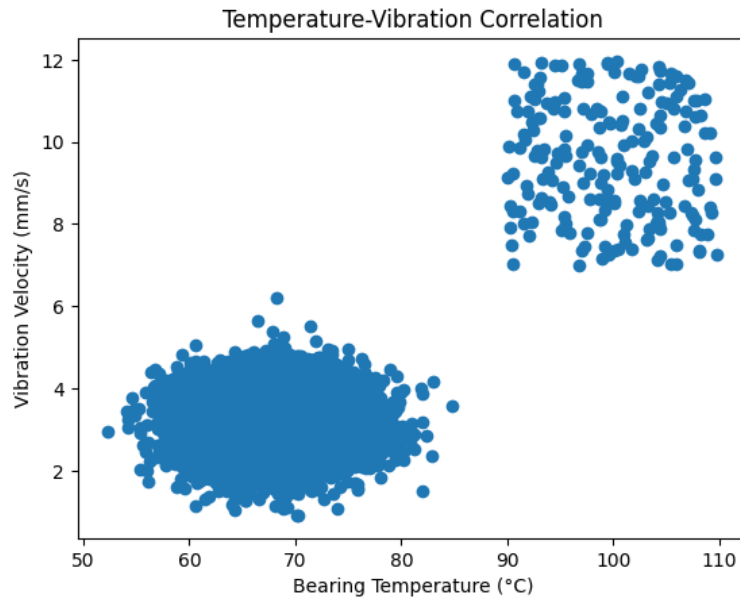


Figure 4. Coupled vibration–temperature dynamics demonstrating friction-induced thermal growth during degradation onset.

A scatter correlation plot between transmitted torque and vibration velocity is provided in Figure 5. The near-linear trend validates the regression findings and confirms torque as a precursor to structural excitation.

Importantly, several high-torque points precede vibration spikes, indicating a predictive window suitable for proactive maintenance interventions.[7]

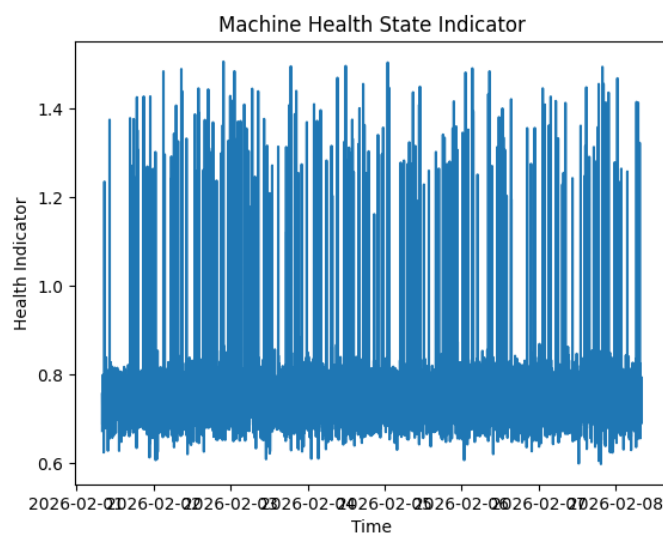


Figure 5. Correlation between transmitted torque and vibration velocity revealing torque escalation as an early fault indicator.



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## 6. Discussion

The graphical analysis confirms that multi-domain sensing substantially improves fault observability compared with single-parameter monitoring. In particular, the combination of torque-derived indicators and vibration energy enables earlier detection of instability than temperature measurements alone. The Health State Indicator further simplifies decision-making by translating complex system dynamics into an interpretable scalar metric.

Such visualization not only supports engineering diagnostics but also enhances model transparency — a key requirement for industrial adoption of predictive maintenance technologies.

## 7. Industrial Implications

The methodology aligns with Industry 4.0 principles and supports digital twin architectures. Structured datasets enable future deployment of deep learning models for Remaining Useful Life estimation.

Scalability is straightforward: additional sensors can be incorporated without altering the governing equations.[9]

## 8. Limitations and Future Research

The study relies on modeled rather than field-acquired signals. Future work should include spectral diagnostics, nonlinear observers, and transformer-based temporal models.

Adaptive thresholds driven by reinforcement learning represent another promising direction.

## 9. Conclusion

A physics-informed hybrid modeling framework for monitoring a gearbox-driven cotton gin machine has been developed. By merging nonlinear mechanics, thermal dynamics, Kalman filtering, and regression analytics, the approach delivers interpretable and accurate health assessment.

The results confirm that vibration energy and bearing temperature are primary degradation indicators, while torque acts as an early-warning variable. Adoption



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of this methodology may significantly enhance reliability, reduce maintenance costs, and accelerate the transition toward intelligent cotton processing plants.

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