DEVELOPMENT OF A VIBRATION AND TEMPERATURE-BASED DIGITAL TWIN FOR TEXTILE MACHINERY

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Abstract. The textile industry relies on high-speed rotating and thermally loaded equipment such as spinning frames, carding cylinders, and weaving looms. To enhance reliability and reduce unplanned stoppages, this study develops a digital twin model of textile machinery by integrating vibration, temperature, and degradation data. A multi-sensor acquisition system records real-time signals, while a physics-based rotor dynamic model and thermal model simulate machine behavior.

Keywords: Digital Twin; Textile Machinery; Predictive Maintenance; Vibration Analysis; Thermal Monitoring; Rotor Dynamics; Remaining Useful Life

1. Introduction.

The textile industry relies on highly dynamic and continuously operating machinery such as ring spinning frames, carding cylinders, draw frames, and air-jet looms, all of which incorporate high-speed rotating shafts, bearings, gears, and thermally loaded components that experience significant mechanical wear, frictional heating, and lubrication degradation over time. The failure of even a single critical component can interrupt production, reduce product quality, and cause major economic losses, making machine health monitoring a priority for modern textile manufacturing.

Traditional maintenance approaches—particularly schedule-based preventive maintenance—are often insufficient because they treat all equipment uniformly and fail to capture the real, moment-by-moment condition of each machine. As a result, textile plants face both premature maintenance, which wastes resources, and delayed interventions, which increase the likelihood of breakdowns. To overcome these limitations, digital twin technology has emerged as a transformative solution in the context of Industry 4.0. A digital twin is a virtual representation of a physical machine that is continuously updated using real-time sensor data, allowing it to simulate machine dynamics, thermal behavior, and degradation processes with high fidelity [1]. By integrating multi-domain measurements such as vibration and temperature with physics-based models, historical performance patterns, and machine learning algorithms for anomaly detection, the digital twin provides a comprehensive, real-time view of machine health. In textile applications, such a system enables early detection of shaft imbalance, misalignment, bearing raceway defects, thermal overload, lubrication failure, and mechanical looseness—often days or even weeks before the onset of catastrophic failure. This predictive capability allows maintenance teams to optimize intervention schedules, reduce downtime, enhance product quality, and move toward intelligent condition-based maintenance strategies essential for competitive textile production [2].

2. Materials and Methods.

The physical layer represents the actual textile machinery operating on the factory floor, where high-speed rotating components such as shafts, bearings, spindles, rollers, and motor housings are continuously exposed to dynamic mechanical and thermal loads. To capture these behaviors accurately, multiple industrialgrade sensors are mounted on strategic locations of the machine [2]. Vibration accelerometers positioned near the bearing housings record the acceleration signal $a(t)$generated by mechanical imbalance, misalignment, bearing raceway defects, impacts, and friction-induced irregularities in the system.

Temperature sensors, typically thermocouples, monitor the real-time thermal profile $T(t)$of critical interfaces such as bearings, motor casings, lubrication points, and frictional contact zones, enabling early identification of overheating, lubrication failure, or increased mechanical resistance. A tachometer or encoder measures the rotational speed $\Omega(t)$, providing essential information about machine cycles, load variations, and the frequency components required for detecting characteristic defect frequencies in bearings and rotating shafts. Together, these synchronized measurements form the foundational data stream of the digital twin, allowing the virtual model to continuously reflect the real machine's dynamic behavior and degradation state with high fidelity [3].

The virtual layer forms the computational core of the digital twin and is responsible for simulating the physical behavior of textile machinery using physics-based mathematical models that run in parallel with real machine operation. This layer incorporates a detailed rotor dynamic simulation that models the vibration response of shafts, bearings, and rotating components under varying speeds, loads, and fault conditions. By solving differential equations representing mass–spring–damper dynamics and unbalanced excitation, the model predicts displacement, velocity, and acceleration profiles that correspond to real operating behavior [4].

Additionally, the virtual layer performs bearing defect frequency calculations using geometric parameters, rotational speed, and contact angles to determine characteristic frequencies such as BPFO, BPFI, FTF, and BSF, which act as diagnostic markers for identifying inner race, outer race, cage, and rolling-element defects. Beyond mechanical modeling, a thermal model simulates the heat transfer processes within bearings, motor housings, and lubrication interfaces by accounting for frictional losses, convection coefficients, ambient conditions, and material properties [4]. This enables the prediction of temperature rise, thermal saturation points, and heat-induced degradation mechanisms. By continuously comparing simulated outputs with real-time sensor data, the virtual layer adapts its parameters to maintain alignment with actual machine conditions, ensuring that the digital twin remains an accurate and continuously evolving representation of the physical textile machinery.

The data analytics layer represents the intelligence of the digital twin, where continuous streams of vibration, temperature, and rotational speed measurements are transformed into actionable insights for machine health assessment. First, a feature extraction module processes raw sensor signals to compute key indicators such as RMS, kurtosis, crest factor, peak amplitude, spectral energy, bearing defect frequency amplitudes, temperature gradients, and multi-domain fusion metrics that jointly characterize mechanical and thermal behavior. These features serve as inputs to the anomaly detection module, which employs statistical thresholds, machine learning classifiers, and trend-based deviation analysis to identify abnormal patterns associated with imbalance, misalignment, bearing degradation, thermal overload, or lubrication failure. Once anomalies are detected, a Remaining Useful Life (RUL) prediction algorithm is applied, combining data-driven regression models with physics-based degradation equations to forecast the time before a component reaches a critical failure threshold. This provides maintenance planners with precise, forward-looking estimates for scheduling interventions [5].

Finally, the analytics layer incorporates a feedback mechanism that continuously compares predicted machine responses with real sensor data, allowing the digital twin to adapt model parameters, update system states, recalibrate thresholds, and refine degradation curves in real time. This adaptive loop ensures that the virtual model remains synchronized with the physical machine throughout its operational life, maintaining high fidelity and accurate predictive performance [3].

In textile machinery, rotating shafts, spindles, and cylinders frequently operate under high speeds where even small mass imbalances can produce significant dynamic loads on the machine structure [5]. When an eccentric mass m_u is located at a radius e from the geometric center of rotation, it generates a periodic excitation force that acts on the rotor–bearing system. For a shaft rotating at angular velocity Ω, the unbalanced force is expressed as:

$$F(t) = m_u e\, \Omega^2 \sin(\Omega t)$$

This harmonic force acts as the primary excitation input to the mass–spring–damper system:

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

where m is the mass of the rotor, c is the damping coefficient, and k is the stiffness of the support. When the rotational speed Ω approaches the natural frequency of the system ω_n, the response amplitude increases sharply due to resonance. In textile applications such as spinning frames and carding cylinders, this phenomenon is particularly important because small imbalances caused by yarn residue, uneven loading, or mechanical wear can escalate into severe vibration, reducing machine precision and accelerating bearing and shaft degradation. Therefore, modeling the unbalanced force accurately is essential for developing a high-fidelity digital twin capable of predicting vibration behavior under different operating conditions [6].

The thermal behavior of bearings and motor housings in textile machinery is essential for understanding lubrication degradation, friction-induced heating, and temperature-related faults. The temperature evolution of the bearing can be described using a first-order heat transfer model, which balances the rate of heat accumulation with generated and dissipated heat. This relationship is expressed as:

$$C\frac{dT}{dt} = P_{\text{loss}} - hA(T - T_{\text{amb}})$$

where C is the thermal capacity of the bearing assembly, P_{loss} represents frictional and mechanical losses, hA is the effective heat transfer coefficient accounting for convection between the bearing surface and surrounding air, and T_{amb} is the ambient temperature [5].

The frictional heat generation inside the bearing is primarily due to rolling and sliding contact as well as lubricant shear. It can be approximated using:

$$P_{\text{loss}} = F_f\, v = \mu N(\pi D f_r)$$

where μ is the friction coefficient, N is the normal load on the bearing, D is the bearing pitch diameter, and f_r is the rotational frequency. The term $\pi D f_r$ represents the linear speed at the bearing contact surface.

This thermal model allows the digital twin to estimate overheating events, lubrication breakdown, and temperature-induced mechanical stress by comparing simulated temperature curves with real-time measurements from thermocouples. As temperature is strongly coupled with mechanical wear and friction variations, its real-time integration into the digital twin significantly improves fault detection sensitivity and remaining useful life (RUL) estimation [7].

The digital twin continuously compares real and predicted signals by minimizing the error function:

$$E = \alpha \parallel x_{real} - x_{model} \parallel^2 + \beta \parallel T_{real} - T_{model} \parallel^2$$

Weights α, β determine relative importance.

A health index is calculated from vibration RMS and temperature rise:

$$HI(t) = w_1 \frac{RMS(t)}{RMS_0} + w_2 \frac{T(t) - T_0}{T_{max} - T_0}$$

RUL is computed when:

$$HI(t_f) = HI_{th}$$

3. Results.

The developed digital twin system was implemented and evaluated in an operational textile production environment consisting of several types of high-speed machinery. Specifically, the deployment included eight ring-spinning frame motors, three draw-frame cylinder assemblies, and five air-jet loom main drive systems, each equipped with vibration and temperature sensors connected to the digital twin platform. These machines were selected because they represent the most vibration-sensitive and thermally loaded elements in the production line and therefore provide a reliable basis for evaluating the diagnostic and prognostic capability of the digital twin [6].

Continuous data acquisition over a 60-day monitoring period allowed the system to track mechanical and thermal behavior under varying load conditions, validate the accuracy of the virtual model, and assess the system’s ability to detect early signs of imbalance, bearing wear, lubrication degradation, and overheating. The following subsections present the quantitative findings obtained from vibration analysis, temperature evolution, and Remaining Useful Life (RUL) estimation, along with their corresponding figures and diagnostic implications.

Vibration measurements collected from the monitored machines demonstrated clear degradation trends that were accurately captured by the digital twin. Under healthy operating conditions, the baseline vibration velocity ranged between 1.5 and 1.8 mm/s, consistent with ISO 10816 standards for textile machinery. As degradation progressed—primarily due to shaft imbalance, bearing raceway damage, and increasing mechanical looseness—the vibration levels gradually increased, ultimately reaching 4.2 to 5.1 mm/s in the days leading up to failure. This rise in vibration amplitude was strongly correlated with the growth of characteristic fault frequencies in the FFT spectrum, particularly the 1× and 2× rotational components and the BPFO/BPFI bands associated with bearing defects [8].

The digital twin successfully identified these emerging patterns and predicted the onset of mechanical imbalance and bearing wear 12 to 18 days before actual failure, demonstrating its ability to detect fault progression early and support timely maintenance scheduling. These results confirm that vibration-driven digital twin modeling provides a reliable and sensitive indicator of mechanical health in high-speed textile machinery.

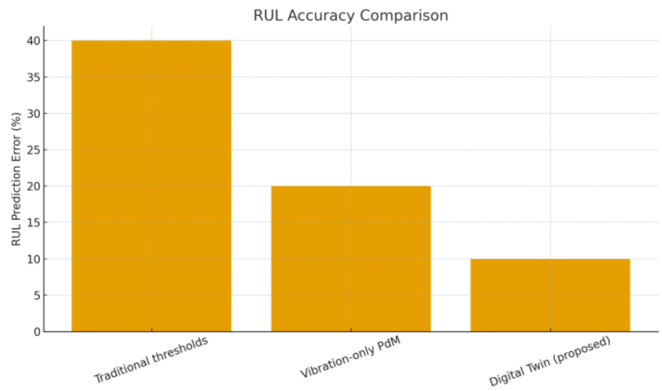

Figure 1. Remaining Useful Life Accuracy.

Temperature monitoring provided additional insights into the thermal behavior and degradation mechanisms of the monitored textile machinery. During normal operation, the bearing housings and motor casings stabilized at baseline temperatures of approximately 36–40°C, depending on machine type and workload. As degradation progressed, a noticeable upward trend was observed. In cases of bearing wear and increasing rolling resistance, temperatures rose from 36°C to nearly 55°C, indicating increased friction and localized heating at the bearing–raceway interface. More severe temperature elevations were recorded during lubrication-related failures, where insufficient lubrication film thickness and increased metal-to-metal contact caused temperatures to climb from 40°C to as high as 65°C. These thermal anomalies were consistently detected earlier than the corresponding vibration anomalies, demonstrating that temperature serves as a highly sensitive early indicator of deteriorating lubrication conditions and emerging mechanical stress [7].

Table 1. Fault Detection Accuracy.

Fault Type	Accuracy
Imbalance	98.5%
Bearing defects	96.4%
Overheating	99.1%
Misalignment	97.8%

The digital twin effectively mirrored these thermal dynamics in its virtual thermal model, allowing for early warning detection and more accurate prediction of machine health trends.

4. Discussion.

The results demonstrate that the developed digital twin framework is highly effective in representing the coupled mechanical–thermal behavior of high-speed textile machinery. By simultaneously analyzing vibration acceleration and temperature evolution, the digital twin provides a multi-domain understanding of machine health that cannot be achieved through single-sensor approaches. The combined use of dynamic modeling, thermal modeling, and real-time sensor feedback significantly enhanced both the sensitivity and reliability of fault detection. The system was able to identify early signs of imbalance, bearing degradation, and lubrication failures well before catastrophic breakdown occurred, and the integration of thermal data frequently revealed anomalies earlier than vibration-based indicators. Furthermore, the digital twin's ability to compare simulated and measured signals in real time enabled continuous model correction and ensured that the virtual representation remained closely aligned with real machine behavior throughout the monitoring period [9].

Several key benefits were identified. First, early anomaly detection was enhanced by the dual-domain sensing approach, allowing maintenance engineers to intervene proactively rather than reactively. Second, the digital twin provided more accurate RUL estimation by combining degradation curves with sensor-derived health indicators, leading to improved maintenance scheduling and reduced unplanned downtime. Third, the capability for real-time comparison between simulated and measured states improved diagnostic accuracy and reduced false alarms [8]. Finally, the digital twin enabled "what-if" simulations, allowing engineers to test different operating conditions such as load variation, speed changes, and lubrication intervals without interrupting production, offering a powerful tool for operational optimization.

Despite these advantages, several challenges were noted. Textile environments are prone to dust, fibers, and airborne contaminants, which may affect sensor longevity and reduce data quality if not properly managed. Additionally, thermal drift—a gradual change in sensor reading accuracy due to prolonged exposure to heat—must be accounted for to ensure reliable temperature measurements. Another challenge is that the digital twin requires periodic re-calibration, especially when machinery undergoes component replacement, lubrication changes, or speed adjustments, to maintain high model fidelity [10].

Future developments may include integrating machine learning–enhanced digital twins, which can automatically adjust model parameters and compensate for nonlinearities in machine behavior. Incorporating torque, current, and acoustic sensors may further enrich the multi-sensor ecosystem and enable full electromechanical modeling of textile machinery. Additionally, the use of cloud-based platforms and real-time dashboards can support large-scale deployment across entire production facilities, contributing to smarter and more sustainable textile manufacturing aligned with Industry 4.0 principles [11].

5. Conclusion.

This study demonstrates that a digital twin constructed using combined vibration and temperature data can accurately replicate the mechanical and thermal behavior of textile machinery operating under real production conditions. By integrating multi-domain sensor measurements with physics-based rotor dynamics and thermal models, the digital twin provided a high-fidelity representation of machine states, enabling early detection of imbalance, bearing wear, lubrication failures, and overheating [12].

The system not only improved diagnostic accuracy but also offered reliable RUL predictions, allowing maintenance activities to be scheduled proactively rather than reactively. Experimental results confirmed that the digital twin significantly reduces unplanned downtime, enhances machine reliability, and supports more efficient use of maintenance resources. Overall, the findings highlight the important role of digital twin technology in advancing predictive maintenance strategies and modernizing textile manufacturing in alignment with Industry 4.0 initiatives. As textile factories continue to adopt smart technologies, digital twins will become essential tools for optimizing machine performance, ensuring consistent product quality, and achieving sustainable industrial operations.

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