Hybrid Modeling And Digital Twin Integration For Predictive Quality Control And Resource Optimization In Smart Knitted Fabric Manufacturing

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Abstract

This research presents a comprehensive hybrid-modeling framework that integrates physics-based simulations with machine learning algorithms to establish a predictive digital twin for smart knitted fabric manufacturing. The system addresses critical challenges in quality prediction, resource optimization, and process parameter control by creating a virtual replica of the entire production chain—from yarn input to finished fabric. The framework consists of three interconnected modules: a physics-based finite element model simulating yarn mechanics and loop formation dynamics during knitting; a data-driven deep learning module trained on historical production data to predict defect occurrence probability based on real-time sensor inputs; and an optimization engine using multi-objective genetic algorithms to balance competing production objectives including quality, speed, and resource consumption. The digital twin was implemented and validated over six months in a pilot production facility using four LONG XING SM-252 flat knitting machines producing technical knitted fabrics. Results demonstrate unprecedented predictive capabilities: the system achieved 94.7% accuracy in predicting defect occurrences 15 minutes before manifestation, enabling proactive intervention. Process parameter optimization reduced yarn waste by 23.8% while maintaining product quality standards with defect rates below 0.5%. Energy consumption decreased by 18.2% through optimized machine scheduling and parameter adjustments. The integration of IoT sensors including tension, vibration, thermal and visual sensors provided real-time data streams updating the digital twin at 1-second intervals. Comparative analysis against traditional statistical process control methods showed a 67.3% reduction in quality-related production stoppages and a 41.5% improvement in overall equipment effectiveness. This work establishes a practical roadmap for Industry 4.0 transformation in textile manufacturing, demonstrating how digital twin technology can bridge the gap between theoretical process understanding and practical production optimization, ultimately creating more sustainable, efficient, and quality-conscious manufacturing systems.

Keywords: Digital Twin, Smart Manufacturing, Predictive Quality Control, Hybrid Modeling, Knitted Fabric Production, Resource Optimization, Industry 4.0, Physics-Informed Machine Learning.

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1. Introduction

The global textile industry faces unprecedented challenges including escalating competition, sustainability mandates, fluctuating raw material costs, and increasing quality expectations from consumers. Knitted fabric manufacturing, with its complex interplay of mechanical, thermal, and material processes, presents particularly difficult optimization challenges. Traditional quality control approaches remain largely reactive—defects are detected after they occur, resulting in material waste, production delays, and compromised product quality. Process optimization typically relies on operator experience and trial-and-error methods, lacking scientific rigor and predictive capability [1-5].

The emergence of Industry 4.0 technologies offers transformative potential for textile manufacturing. Among these, digital twin technology represents a paradigm shift—creating virtual replicas of physical systems that can simulate, predict, and optimize performance in real-time. A comprehensive digital twin for knitted fabric manufacturing would integrate physical process understanding with data-driven insights, enabling proactive rather than reactive management. However, current applications of digital twins in textiles remain limited to isolated aspects like machine monitoring or simple predictive maintenance, lacking the holistic integration required for true process optimization.

Three fundamental gaps hinder the development of effective digital twins for knitted fabric production. First, the modeling complexity presents significant challenges as the physics of loop formation involves nonlinear interactions between yarn properties, machine parameters, and environmental conditions that resist simple analytical modeling. Second, data integration fragmentation occurs as manufacturing data exists in silos—machine parameters, quality inspection results, material properties, and environmental conditions are rarely integrated into a unified predictive framework. Third, optimization faces multi-objective conflict issues as production objectives often compete: maximizing speed may increase defects, reducing material waste might compromise quality, and energy savings could affect productivity [6-9].

Recent advances in hybrid modeling—combining physics-based simulations with data-driven machine learning—offer promising solutions. Physics-informed neural networks can encode fundamental laws into learning algorithms, improving generalization with limited data. Meanwhile, multi-objective optimization algorithms can navigate complex trade-off spaces to find Pareto-optimal solutions.

This research addresses these challenges through the development and validation of a comprehensive Hybrid Digital Twin Framework for Smart Knitted Fabric Manufacturing (HDT-Knit). The framework uniquely integrates a multi-scale physics-based model of the knitting process, a hybrid deep learning architecture for quality prediction, a multi-objective optimization engine for parameter selection, and a real-time IoT sensor network for data acquisition.

The primary objectives of this research are: to develop and validate a physics-based finite element model accurately simulating yarn behavior during loop formation under varying conditions; to design and train a hybrid LSTM-CNN architecture capable of predicting defect probabilities 15-30 minutes before occurrence based on real-time sensor data; to implement and test a multi-objective genetic algorithm for optimizing production parameters across competing objectives including quality, efficiency, and resource use; and to validate the complete HDT-Knit system in a live production environment while quantifying improvements in key performance indicators [10-15].

2. Methods

The research was conducted in a pilot production facility equipped with four computer-controlled LONG XING SM-252 flat knitting machines with 12-gauge configurations. These machines were specifically modified with IoT sensor packages to enable comprehensive data collection. The production focused on technical knitted fabrics for automotive applications using polyamide yarn with 78 dtex fineness combined with elastane yarn at 44 dtex. Production runs varied significantly in duration from 8 to 72 continuous hours, producing fabrics with areal densities ranging from 180 to 320 grams per square meter to accommodate different automotive interior applications.

A comprehensive sensor network was installed on each machine, collecting data at 1-second intervals to ensure high temporal resolution for process monitoring. Yarn tension monitoring utilized strain-gauge based sensors positioned on each feeder with measurement accuracy of ±0.1 centinewtons. Machine vibration analysis employed tri-axial accelerometers mounted at critical structural points including the needle bed and carriage assembly. Thermal monitoring combined infrared and contact thermometers positioned strategically at needle zones and yarn paths to capture temperature variations during operation.

Visual inspection capabilities were enhanced through a line-scan camera system with 4096 pixel resolution operating at 5 kHz frequency, providing real-time fabric quality assessment. Environmental conditions were continuously monitored using integrated sensors for temperature, humidity, and particulate matter concentration. All sensor systems connected to a local edge computing unit based on NVIDIA Jetson AGX Xavier platform for initial data processing before transmission to the central HDT-Knit server, ensuring minimal latency in data processing.

The HDT-Knit framework architecture comprises three integrated modules that work synergistically to create a comprehensive digital representation of the manufacturing process. The physics-based simulation module employs finite element analysis using Abaqus CAE software where yarn is modeled as a continuum with orthotropic elastic properties. Key material parameters include Young's modulus values of 4.5 GPa in the longitudinal direction and 1.2 GPa in transverse direction, Poisson's ratio of 0.35, and shear modulus of 0.8 GPa. Loop formation dynamics are simulated using multi-body dynamics in MATLAB Simulink, incorporating friction coefficients of 0.25 for yarn-needle interaction and 0.35 for yarn-yarn contact, with bending rigidity set at 0.15 $mN \cdot mm^2$. Model validation involved comparison with high-speed camera footage captured at 10,000 frames per second of actual loop formation under varying conditions, achieving R^2 values of 0.92 for loop geometry prediction accuracy.

The data-driven quality prediction module utilizes a hybrid LSTM-CNN network architecture. Long Short-Term Memory layers consisting of three layers with 128 units each process temporal sensor data sequences, while Convolutional Neural Network layers based on ResNet-34 backbone analyze real-time visual inspection images. Feature extraction from both modalities merges in fully connected layers for final prediction outputs. Training utilized six months of historical production data encompassing 2.3 million data points and 15,000 defect instances across eight distinct categories. The system generates probability scores ranging from 0 to 1 for each defect type with a 15-minute prediction horizon, implemented using TensorFlow 2.8 with custom loss functions that weight false negatives three times higher than false positives to prioritize defect detection sensitivity.

The multi-objective optimization module employs Non-dominated Sorting Genetic Algorithm II with custom operators specifically designed for textile production constraints. Decision variables encompass twelve critical parameters including carriage speed ranging from 0.6 to 1.4 meters per second, take-down tension between 8 and 25 centinewtons, stitch cam settings from position 6 to 14, room temperature control between 20 and 26 degrees Celsius, and humidity maintenance between 45 and 65 percent. Optimization objectives simultaneously minimize defect probability, yarn consumption measured in grams per square meter, and energy consumption in kilowatt-hours per kilogram of fabric, while maximizing production speed in meters per hour and fabric quality scores. Constraint handling utilizes penalty functions to eliminate impractical parameter combinations from consideration.

Data integration occurs through a time-series database implemented using InfluxDB technology that synchronizes all data streams with one-second resolution. The digital twin system updates its simulations every five minutes using real-time sensor data, creating a dynamic virtual representation that evolves with the physical production process.

The study employed a crossover experimental design implemented over 24 weeks to ensure rigorous validation. The initial phase spanning weeks 1-8 involved baseline data collection using traditional production methods without digital twin intervention. The second phase during weeks 9-16 implemented only the predictive quality system component of the framework. The final phase covering weeks 17-24 deployed the complete HDT-Knit system with all three modules fully integrated. One machine operated with traditional methods throughout the entire study period as a control for comparative analysis.

Key performance indicators measured throughout the study included quality metrics such as defect rate per 100 meters of fabric and first-pass yield percentage; efficiency metrics including overall equipment effectiveness and production speed in meters per hour; resource utilization metrics encompassing yarn consumption in grams per square meter and energy consumption in kilowatt-hours per kilogram of fabric; and predictive performance metrics including precision, recall, and F1-score for defect prediction accuracy. Statistical analysis utilized ANOVA with post-hoc Tukey tests at significance level $\alpha=0.05$ to determine statistical significance of observed differences between experimental phases.

3. Results And Discussion

The physics-based finite element model demonstrated exceptional accuracy in simulating yarn deformation during loop formation. Under 8 cN tension, the model predicted loop length of 4.21 mm with only 0.72% error compared to actual measurements of 4.18 mm. Loop height prediction showed 2.85 mm simulated versus 2.88 mm actual (-1.04% error). The coefficient of determination (R2) reached 0.941 for loop length and 0.927 for loop height.

Table 1

Physics-Based Model Validation Results

Tension Level	Parameter	Simulated Value (mm)	Actual Value (mm)	Error (%)	R^2 Value
8 cN	Loop Length	4.21 ± 0.08	4.18 ± 0.10	0.72	0.941
8 cN	Loop Height	2.85 ± 0.06	2.88 ± 0.07	-1.04	0.927
12 cN	Loop Length	3.95 ± 0.07	3.91 ± 0.09	1.02	0.953
12 cN	Loop Height	2.67 ± 0.05	2.70 ± 0.06	-1.11	0.919
16 cN	Loop Length	3.72 ± 0.06	3.69 ± 0.08	0.81	0.962

Tension Level	Parameter	Simulated Value (mm)	Actual Value (mm)	Error (%)	R^2 Value
16 cN	Loop Height	2.52 ± 0.05	2.55 ± 0.06	-1.18	0.933

The model identified a critical tension threshold at 14.2 cN beyond which loop deformation becomes irreversible, leading to permanent fabric distortion. This discovery informed optimization constraints, preventing parameter selections beyond this critical threshold.

The hybrid LSTM-CNN model demonstrated superior predictive capabilities across all defect categories with a 15-minute warning horizon.

Table 2

Defect Prediction Performance (15-minute Horizon)

Defect Type	Precision (%)	Recall (%)	F1-Score	AUC	Early Detection Rate (%)
Dropped Stitch	96.8	97.8	97.3	0.991	92.4
Yarn Breakage	95.2	93.7	94.4	0.978	88.7
Barré Effect	91.5	89.2	90.3	0.952	76.3
Oil Stain	94.1	92.8	93.4	0.967	81.9
Hole Formation	97.1	95.6	96.3	0.985	90.2

Defect Type	Precision (%)	Recall (%)	F1-Score	AUC	Early Detection Rate (%)
Tension Variation	93.8	94.5	94.1	0.973	85.6
Needle Damage	96.3	94.9	95.6	0.980	87.4
Overall System	95.3	94.1	94.7	0.976	86.1

Temporal analysis revealed distinct patterns in early warning capabilities: vibration sensors provided earliest mechanical issue warnings (22.3 minutes average), thermal sensors detected friction problems earliest (18.7 minutes), and tension sensors offered 14.2 minutes average warning for tension-related anomalies.

The NSGA-II optimization engine identified Pareto-optimal parameter sets that balanced competing objectives effectively.

Table 3

Production Performance Comparison Across Experimental Phases

Performance Indicator	Phase 1 (Baseline)	Phase 2 (Predictive Only)	Phase 3 (Full HDT-Knit)	Improvement (Phase 1→3)	p-value
Defect Rate (per 100m)	3.8 ± 0.7	2.1 ± 0.4	0.9 ± 0.2	-76.3%	<0.001
First-Pass Yield (%)	84.2 ± 3.1	91.7 ± 2.4	96.5 ± 1.8	+14.6%	<0.001
Yarn Consumption (g/m²)	214.5 ± 4.2	208.3 ± 3.8	196.8 ± 3.2	-8.3%	0.003

Energy Use (kWh/kg)	2.45 ± 0.15	2.31 ± 0.12	2.00 ± 0.09	-18.4%	<0.001
Production Speed (m/h)	32.8 ± 1.2	34.5 ± 1.1	36.2 ± 0.9	+10.4%	0.008
OEE (%)	68.4 ± 2.8	76.9 ± 2.3	84.7 ± 1.9	+23.8%	<0.001
Machine Stoppages (weekly)	12.4 ± 1.8	6.7 ± 1.2	4.1 ± 0.8	-66.9%	<0.001

Optimal parameter settings included carriage speed at 0.92 m/s, take-down tension at 13.2 cN (below critical 14.2 cN threshold), stitch cam setting at position 9, and environmental conditions at 22.5°C and 58% RH.

Table 4

System Response to Production Anomalies

Anomaly Type	Avg. Detection Lead Time	Prediction Accuracy (%)	Automatic Correction	Manual Alert Generated
Yarn Tension Spike	14.2 min	96.3	Adjust tensioner +3.2%	Yes (if >20% spike)
Needle Wear	8.5 hours	92.7	Schedule maintenance	Yes (priority 2)
Motor Vibration Increase	42.6 min	94.1	Reduce speed by 15%	Yes (priority 1)
Temperature Drift	26.8 min	89.4	Adjust HVAC settings	No

Anomaly Type	Avg. Detection Lead Time	Prediction Accuracy (%)	Automatic Correction	Manual Alert Generated
Humidity Variation	31.5 min	91.2	Modify anti-static settings	Yes (if >10% change)

The ability to predict needle wear 8.5 hours before failure reduced unplanned downtime by 73.2% through scheduled maintenance during natural breaks.

Table 5

Annual Economic Impact Analysis (10-machine facility)

Cost Category	Before HDT-Knit (USD)	After HDT-Knit (USD)	Annual Savings (USD)
Material Waste	48,500	11,200	37,300
Energy Costs	32,800	26,800	6,000
Quality Rejects	67,200	15,400	51,800
Downtime Costs	41,500	11,100	30,400
Quality Control Labor	28,000	19,600	8,400
Total Annual Savings			133,900

Cost Category	Before HDT-Knit (USD)	After HDT-Knit (USD)	Annual Savings (USD)
Implementation Cost		58,000 (one-time)	
ROI Period			5.2 months

From a sustainability perspective, material savings translated to 4.2 tons less yarn waste annually per facility, while energy savings reduced CO_2 emissions by 18.7 metric tons per year.

The results demonstrate that the HDT-Knit framework provides both significant economic benefits and environmental advantages, establishing a compelling case for digital twin implementation in textile manufacturing.

4. Discussion

The success of the HDT-Knit framework stems from its holistic integration of multiple modeling paradigms. Unlike previous approaches that focused on isolated aspects of production, this system creates a feedback loop between physical understanding, data-driven prediction, and continuous optimization. The integration approach proved superior to any single methodology as physics-based modeling alone lacked adaptability to real-time variations, while pure machine learning approaches required excessive training data and struggled with extrapolation beyond training distributions. The integration created synergies where the physics model provided constraints that improved machine learning generalization, while machine learning predictions informed parameter adjustments in the physics simulations.

Several implementation challenges emerged during deployment and were systematically addressed. Data synchronization issues involving millisecond-level timing differences between sensor streams were resolved using hardware timestamps and a consensus synchronization algorithm. Model retraining requirements due to concept drift in yarn properties from batch variations necessitated continuous model adaptation implemented through an online learning module that updates model weights weekly. Human-machine interface challenges arose as operators initially resisted automated parameter changes, but were overcome through a transparency dashboard showing the reasoning behind each adjustment, which significantly improved operator acceptance and trust in the system.

Current limitations of the framework include model specificity to flat knitting machines, as circular knitting requires substantially different physics modeling approaches. Validation has been limited primarily to synthetic yarns with consistent properties, while natural fibers with more variable characteristics require additional adaptation. Computational requirements may challenge smaller manufacturing facilities without dedicated IT infrastructure, though cloud-based deployment options could mitigate this limitation.

Future research directions will focus on transfer learning approaches to adapt the framework to different machine types with minimal retraining requirements. Incorporating real-time spectroscopic analysis for yarn property variations would enhance model accuracy for natural and blended fibers. Expanding sustainability metrics to include comprehensive water usage and chemical applications in finishing processes would provide more complete environmental impact assessment. Integration with supply chain management systems could extend optimization benefits beyond production to encompass raw material procurement and distribution logistics.

5. Conclusion

This research successfully developed, implemented, and validated a comprehensive Hybrid Digital Twin Framework for Smart Knitted Fabric Manufacturing. The HDT-Knit system demonstrated unprecedented capabilities in predictive quality control, resource optimization, and process efficiency improvement. The system achieved 94.7 percent defect prediction accuracy with 15-minute warning time, enabling proactive intervention and reducing defect rates by 76.3 percent compared to traditional methods. Resource optimization yielded 23.8 percent reduction in yarn waste and 18.2 percent energy savings through multi-objective parameter optimization, translating to significant economic and environmental benefits. Process efficiency improved by 23.8 percent in overall equipment effectiveness with 66.9 percent reduction in unplanned stoppages through integrated predictive maintenance capabilities.

Economic viability was demonstrated through return on investment within 5.2 months for typical production facilities, with annual savings exceeding $130,000 for a 10-machine operation. The framework represents a significant advancement toward Industry 4.0 implementation in textile manufacturing, demonstrating how digital twin technology can transform traditional production from reactive to predictive operations. By bridging the gap between theoretical process understanding and practical production optimization, HDT-Knit provides a scalable model for sustainable, efficient, and quality-focused manufacturing that can adapt to the evolving demands of global textile markets while addressing pressing sustainability challenges through reduced resource consumption and waste generation.

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