RESEARCH ARTICLE OPEN ACCESS

Yarn Breakage Prediction using ML in Spinning Mills

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Abstract:

Yarn breakage during textile manufacturing processes such as weaving and spinning represents a critical challenge that significantly impacts production efficiency, product quality, and operational costs. This paper provides a comprehensive review of yarn breakage prediction methodologies, tracing the evolution from empirical and statistical approaches to contemporary machine learning techniques. We examine the fundamental mechanisms of yarn breakage, including the complex stresses that warp and weft yarns undergo during weaving processes. The review synthesizes research on traditional prediction methods, artificial neural network applications, and recent advances in automated machine learning and explainable artificial intelligence for yarn breakage forecasting. A detailed analysis of a pioneering 2022 study demonstrates how Industry 4.0 concepts, Internet of Things data, and Auto-ML tools can achieve predictive performance with R^2 values up to 0.73 for weft break prediction. The paper also discusses practical implications for textile manufacturers, including preventive measures enabled by accurate breakage predictions, and identifies future research directions in this rapidly evolving field.

Keywords: Yarn breakage prediction, machine learning, textile manufacturing, Industry 4.0, neural networks, explainable AI.

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I. INTRODUCTION

The textile industry faces a major challenge in **yarn breakage**, which disrupts production, lowers efficiency, and raises costs. Breakages occur during weaving and spinning, often signalling deeper issues with yarn quality, machine condition, or process settings. Predicting these failures before they happen allows manufacturers to take preventive steps—like adjusting machine speed, monitoring specific looms, or modifying yarn inputs—rather than reacting after costly downtime. With the rise of Industry 4.0, IoT sensors now provide continuous machine data, while AI and machine learning analyse patterns to anticipate breakages. Recent studies show that automated ML can successfully predict weft breaks, warp breaks, and yarn bursts, marking a shift from traditional empirical rules to proactive, data-driven quality management. This review highlights the evolution of prediction methods, practical implications for manufacturers, and promising directions for future research.

II. MECHANISMS AND CAUSES OF YARN BREAKAGE

Yarn breakage in textile manufacturing arises from the interplay of mechanical, thermal, and frictional forces acting on fibres. These stresses vary depending on the process—such as spinning, weaving, or knitting—and the type of machinery used. Uneven tension, sudden load changes, and abrasive contact points intensify the risk of rupture. Understanding these mechanisms is crucial for developing reliable prediction models that enhance efficiency and reduce production losses. Stress Factors in Weaving Processes.

A. Stress Factors in Weaving Processes

During weaving, warp yarns—those running lengthwise in the fabric—experience particularly severe mechanical demands. Research has identified five primary types of stress that warp yarns must withstand: tensile stress from tensioning systems, cyclic-extension stress from repeated shedding motions, compression stress from beat-up mechanisms, bending stress around heddles and reeds, and abrasion stress from contact with machine components and other yarns.

The capacity of yarns to endure these combined stresses without breaking is termed "wearability". This property depends on numerous factors including yarn composition, twist level, hairiness, strength, and the effectiveness of sizing treatments applied to protect warp yarns during weaving. Sizing, which involves coating yarns with protective films, plays a particularly critical role in determining wearability and breakage rates.

Weft yarns, inserted across the width of the fabric, face different but equally challenging conditions. They must withstand the mechanical action of insertion systems, whether by shuttle, rapier, projectile, or air jet, and must integrate properly with warp yarns at the fabric formation point. Weft breakages often relate to issues with yarn package quality, tension variations during insertion, or incompatibilities between yarn properties and insertion system characteristics.

B. Breakage Mechanisms in Spinning

In spinning processes, particularly ring spinning which remains the most widely used technology, yarn breakage occurs through different mechanisms. The end breakage rate in ring spinning is a critical parameter that affects maximum spindle speed, indicates yarn quality, reflects machine mechanical condition, and signals raw material quality issues.

Breakages during spinning typically result from weak points in the yarn, excessive tension due to improper drafting or twist insertion, traveller problems, or issues with roving quality. The dynamic nature of ring spinning, with yarn twisting and winding occurring simultaneously at high speeds, creates complex stress conditions that challenge prediction efforts.

C. Data Sources for Breakage Prediction

Modern textile manufacturing environments generate vast amounts of data relevant to yarn breakage prediction. IoT sensors on looms and spinning frames can monitor machine speed, tension variations, temperature, humidity, and production rates. Production planning systems provide information about yarn lots, batch numbers, and customer specifications. Quality control systems contribute data on yarn properties measured in laboratories.

The integration of these diverse data sources under Industry 4.0 frameworks creates opportunities for comprehensive predictive modelling that considers both machine conditions and material characteristics simultaneously.

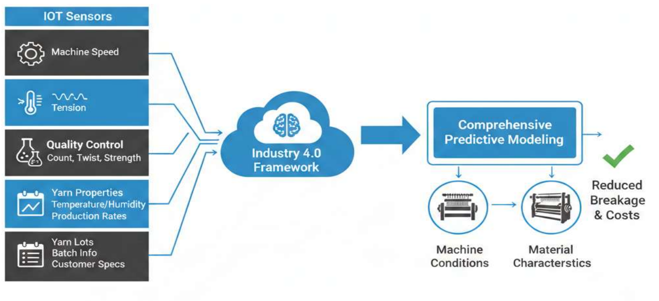

Fig 1: Mechanism and causes of yarn breakage

III. EVOLUTION OF YARN BREAKAGE PREDICTION METHODOLOGIES

The prediction of yarn breakage has evolved significantly over several decades, progressing through three broad methodological approaches: empirical methods based on experience and observation, statistical methods leveraging mathematical relationships, and instrumental methods using specialized testing equipment.

A. Traditional Empirical and Statistical Approaches

Early approaches to predicting yarn breakage relied heavily on empirical knowledge accumulated by experienced textile engineers and operators. These methods included rules of thumb relating breakage rates to yarn count, twist factor, and machine speed. While valuable in practice, empirical approaches lacked precision and could not easily adapt to new yarn types or process conditions.

Statistical methods represented a significant advance by applying mathematical techniques to historical breakage data. Researchers developed regression models relating breakage rates to measurable yarn properties and process parameters. These models could identify statistically significant factors influencing breakages and provide quantitative predictions. However, traditional statistical approaches often struggled with the non-linear relationships and complex interactions characteristic of textile processes.

B. Instrumental Methods and Standardized Testing

Instrumental approaches emerged from efforts to simulate weaving conditions in laboratory settings. The Constant Tension Transport (CTT) instrument, equipped with microprocessor-controlled shedding devices, enables researchers to subject yarns to controlled stresses mimicking those encountered unactual weaving.

These instrumental methods provide valuable first-hand information about yarn performance potential before production begins. By measuring yarn behaviour under simulated weaving conditions, manufacturers can identify problematic yarn lots and adjust sizing treatments or process parameters accordingly. However, instrumental methods cannot capture all the complexities of actual production environments and may not account for interactions between yarns and specific machine conditions.

C. The Emergence of Computational Intelligence

The application of computational intelligence techniques to yarn breakage prediction began with artificial neural networks in the early 2000s. Researchers recognized that neural networks could model the non-linear relationships inherent in textile processes more effectively than traditional statistical methods.

Early neural network applications focused on specific prediction tasks such as forecasting warp breakage rates from sized yarn quality parameters. Feed-forward back-propagation networks with single hidden layers demonstrated good correlation between predicted and actual breakage rates, establishing the viability of neural approaches for this domain.

Subsequent research extended neural network methods to ring spinning applications, using three-layer BP neural network models to predict end breakage rates for polyester/cotton blended yarns. These studies confirmed that neural networks could significantly improve prediction accuracy compared to conventional methods, enabling more efficient production planning and quality control.

IV. MACHINE LEARNING APPROACHES TO YARN BREAKAGE PREDICTION

The current state of the art in yarn breakage prediction centers on machine learning techniques that can automatically discover patterns in complex manufacturing data. A landmark study published in 2022 demonstrates the power of modern machine learning approaches while also highlighting important considerations for practical implementation.

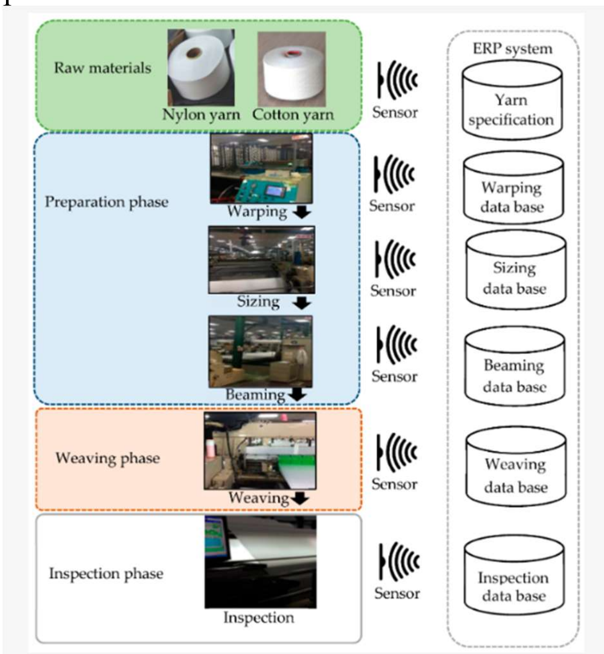

Fig 2: Data collection from textile manufacturing.

A. The Automated Machine Learning Framework

The study, conducted in collaboration with a Portuguese textile company operating under Industry 4.0 principles, addressed three distinct prediction tasks: modelling the number of weft breaks, warp breaks, and yarn bursts during fabric production. The researchers adopted an Automated Machine Learning (Auto-ML) approach to reduce the modelling effort and enable systematic comparison of multiple algorithms

Auto-ML tools automate many of the tedious aspects of machine learning, including algorithm selection, hyperparameter tuning, and feature engineering. The study employed three leading Auto-ML platforms:

H2O, Auto-Gluon, and Auto-Kera's. Each tool explores different model families and optimization strategies, providing a comprehensive view of achievable predictive performance.

B. Experimental Design and Data Considerations

The research utilized historical IoT data collected from industrial looms, encompassing numerous production runs with varying yarn types, machine settings, and environmental conditions. This real-world data presented challenges typical of industrial applications, including missing values, measurement noise, and imbalanced distributions of breakage events.

The experimental design compared two fundamental modelling approaches: single-target regression, where separate models are developed for each breakage type, and multi-target regression, where a single model predicts all three breakage types simultaneously. The researchers also investigated the effect of applying logarithmic transformations to the target variables, which can help when breakage counts follow highly skewed distributions.

C. Results and Model Performance

The experimental results revealed that single-target regression consistently outperformed multi-target approaches across all three prediction tasks. The H2O Auto-ML platform achieved the best overall performance when combined with logarithmic transformation of the target variables. This level of predictive accuracy has substantial practical value. With R^2 of 0.73, manufacturers can confidently identify looms and production conditions associated with elevated breakage risk, enabling targeted preventive interventions. The superiority of single-target regression suggests that the mechanisms driving different breakage types may be sufficiently distinct to warrant separate modelling approaches.

D. The Role of Explainable Artificial Intelligence

A particularly innovative aspect of this research was the application of Sensitivity Analysis explainable Artificial Intelligence (SA XAI) to interpret the trained models. While complex machine learning models can achieve high predictive accuracy, their internal workings often remain opaque, limiting trust and adoption in industrial settings.

The SA XAI approach revealed which input variables most strongly influenced breakage predictions, providing explanatory knowledge about the factors driving yarn failures. This transparency serves multiple purposes: it validates that models are learning physically plausible relationships, it generates insights that can guide process improvements, and it builds operator confidence in acting upon model recommendations.

E. Integration with Production Planning and Control

The ultimate value of yarn breakage prediction lies in its integration with production planning and control systems. When models identify looms or production runs at elevated breakage risk, manufacturers can implement various preventive measures: reducing loom speed to decrease stress on yarns, assigning additional operator attention to problematic machines, substituting yarn lots with better-performing materials, or applying stronger sizing recipes to improve yarn wearability. These interventions represent a shift from reactive to proactive quality management. Rather than responding to breakages after they have already caused downtime and quality defects, manufacturers can anticipate problems and adjust conditions to prevent breakages from occurring.

V. COMPARATIVE ANALYSIS OF PREDICTION METHODS

The diversity of yarn breakage prediction methods raises important questions about selecting appropriate approaches for specific applications. Each method class offers distinct advantages and limitations that should guide selection decisions.

A. Strengths and Limitations of Methodological Approaches

Empirical methods excel in their simplicity and accessibility, requiring no specialized equipment or computational resources. However, they lack precision and cannot easily accommodate new materials or process conditions. Statistical methods provide quantitative predictions and uncertainty estimates but may struggle with non-linear relationships.

Instrumental methods offer controlled simulation of weaving stresses but cannot capture all real-world complexities. Neural networks and machine learning approaches can model complex non-linear relationships and automatically discover relevant patterns, but they require substantial training data and computational resources, and their predictions may be difficult to interpret without explainability techniques.

B. Hybrid Approaches and Method Integration

Emerging evidence suggests that hybrid approaches combining multiple method types may offer advantages over any single technique. For example, instrumental measurements of yarn properties could provide inputs to machine learning models that also incorporate process parameters and machine conditions. This integration leverages the strengths of each approach while compensating for individual limitations.

The Auto-ML framework demonstrated in recent research represents a form of hybrid approach, automatically exploring multiple algorithm types and selecting those best suited to the data characteristics. This methodological pluralism helps ensure that prediction models capture relevant patterns regardless of their specific mathematical form.

VI. PRACTICAL IMPLICATIONS FOR TEXTILE MANUFACTURERS

The advances in yarn breakage prediction have significant implications for textile manufacturing operations, affecting quality management, production planning, and economic performance.

A. Quality Management Applications

Accurate breakage prediction enables proactive quality management throughout the production process. Manufacturers can identify problematic yarn lots before they cause extensive downtime, adjust sizing treatments based on predicted performance, and optimize machine settings for specific yarn types. These capabilities reduce quality variability and improve finished product consistency.

The explanatory insights from XAI techniques also support continuous improvement by identifying root causes of breakage problems. When models reveal that certain machine settings or environmental conditions consistently precede breakages, manufacturers can implement targeted corrective actions that address underlying causes rather than symptoms.

B. Production Planning and Scheduling

Integration of breakage predictions into production planning systems enables more realistic scheduling that accounts for expected downtime. Planners can allocate additional time for jobs involving high-risk yarns or machines, adjust customer delivery commitments based on predicted production efficiency, and make informed decisions about preventive maintenance timing.

The ability to anticipate breakage patterns also supports optimized inventory management. Manufacturers can maintain appropriate stocks of high-performance yarns for critical production runs while using lower-cost materials for applications where breakage risk is acceptable. This data-driven approach reduces waste and ensures resource efficiency.

C. Economic Considerations

The economic case for implementing yarn breakage prediction systems rests on multiple benefit streams. Reduced machine downtime increases productive capacity and reduces per-unit fixed costs. Lower breakage rates decrease operator labour requirements for repair activities. Improved quality reduces waste and customer complaints. Enhanced planning capability enables better asset utilization and inventory optimization.

Implementation costs include investments in sensors and data collection infrastructure, software platforms for modelling and prediction, and training for personnel who will use prediction outputs. The favourable results reported in recent research suggest that these investments can yield attractive returns for manufacturers operating at scale.

VII. FUTURE RESEARCH DIRECTIONS

While significant progress has been made in yarn breakage prediction, numerous opportunities remain for advancing the field through future research.

A. Advanced Machine Learning Techniques

The demonstrated success of Auto-ML approaches opens questions about whether even more sophisticated techniques could improve prediction accuracy. Deep learning architectures such as convolutional neural networks or long short-term memory networks might capture temporal patterns in breakage occurrence that simpler models miss. Transfer learning approaches could enable models developed in one mill to be adapted efficiently for applications in other settings.

B. Real-Time Prediction and Control

Current prediction approaches typically operate on historical data, identifying risk patterns before production begins or between production runs. The extension to real-time prediction, where models continuously monitor sensor data and alert operators to imminent breakage risk, represents an important frontier. Such systems would require low-latency data processing and highly reliable prediction algorithms.

C. Integration with Process Control Systems

Beyond prediction, future systems might automatically adjust process parameters to prevent predicted breakages. Closed-loop control systems that receive breakage risk forecasts and respond by modulating machine speed, tension, or other variables could achieve levels of efficiency and quality impossible with manual intervention.

D. Sustainability Implications

Yarn breakage has sustainability implications through material waste, energy consumption from downtime and restart cycles, and resource use for producing replacement yarns. Research quantifying these impacts and demonstrating how prediction-enabled interventions reduce environmental footprints would support broader adoption of predictive technologies.

VII. CONCLUSION

Yarn breakage prediction has evolved from empirical rules and statistical methods through instrumental approaches to contemporary machine learning techniques that leverage Industry 4.0 data collection and advanced analytics. This evolution reflects both the persistent importance of breakage as a manufacturing challenge and the transformative potential of artificial intelligence in industrial applications.

Recent research demonstrates that automated machine learning tools, applied to IoT data from textile production, can achieve substantial predictive accuracy with R^2 values reaching 0.73 for weft break prediction. The integration of explainable artificial intelligence techniques provides transparency that builds trust and generates actionable insights for process improvement. These capabilities enable manufacturers to shift from reactive breakage management to proactive prevention, with corresponding benefits for quality, efficiency, and cost.

The practical implementation of yarn breakage prediction systems requires attention to data quality, model selection, and integration with production planning and control processes. Manufacturers who successfully navigate these challenges can realize significant competitive advantages through reduced downtime, improved quality, and more efficient operations.

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