RESEARCH ARTICLE OPEN ACCESS

Real-Time Predictive Analytics for Factory Bottleneck Detection Using Edge-Based IIoT Sensors and Machine Learning

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Abstract:

Defect detection and localization remain major challenges in apparel production systems, where small inconsistencies such as yarn tension variation, needle damage, machine vibration anomalies, and fabric density defects can propagate through the supply chain and create substantial quality losses. This study introduces an OTDR-inspired sensor-trace analysis framework that adapts the AI-augmented signal processing approach originally developed for fiber fault localization. The proposed system uses embedded sensors installed on garment production lines to capture real-time vibration, tension, and surface-reflection traces that mimic the waveform-based diagnostic principles used in fiber networks. A convolutional neural network (CNN), trained on over 6,000 simulated and real sensor-trace signatures, automatically identifies defect types such as fabric roll inconsistencies, needle faults, and misalignment anomalies. Experimental results demonstrate a 27–41% improvement in defect localization accuracy over conventional threshold-based QC methods, significantly reducing waste, rework, and production cycle delays. This work provides a scalable and low-cost architecture suitable for modern apparel industries seeking predictive quality control.

Keywords **—** Factory bottleneck detection, IIoT, edge computing, real-time analytics, machine learning, smart manufacturing, predictive monitoring.

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I. Introduction

Modern factories must work fast, stay flexible, and deliver steady output even when demand changes. Every production line depends on many small steps, and each step must finish on time for the next one to start. When one station slows down, the effect moves through the full line. Workers begin to wait, machines stop more often, and the final product takes longer to reach the end. This slowdown is called a bottleneck, and it is one of the main reasons factories lose time and money during daily operations. Most factories still depend on manual checks or delayed reports to detect bottlenecks. Supervisors walk along the line to see where queues are building, or they look at past cycle times to guess which station is falling behind. These methods work for basic monitoring, but they are slow and reactive. By the time a bottleneck is clearly visible, the line may have already lost many minutes of output. Modern production needs a faster and more accurate way to detect early signs of congestion. The growth of IIoT sensors and edge computing offers a new way to solve this problem. Low-cost sensors can capture changes in cycle time, queue length, machine status, and vibration in real time. Edge devices near the machines can process these signals instantly, without depending on a slow cloud network. By using a small machine learning model on these edge devices, factories can predict bottlenecks before they form and respond early. This paper explores a complete system that brings real-time bottleneck prediction into practical factory environments.

A. Background and Motivation

Factories run many machines, tools, and workers at the same time. These stations depend on each other. If one station slows down, the next one must wait.

This waiting builds a queue. When a queue grows for a long time, it becomes a bottleneck. Bottlenecks reduce the full output of the line even if all other stations work well. This is why finding the first signs of a bottleneck is important. Older monitoring systems depend on long reports or manual checks. These methods show problems late. By the time a bottleneck is visible, the line has already lost time. Modern production needs a faster way to see problems as they grow. IIoT sensors can capture cycle time, machine status, queue count, and vibration data in real time. These sensors are low cost and easy to install. Edge devices placed near each station can process the data without sending every raw signal to the cloud. This keeps the delay very low. Machine learning models on these edge devices can learn the normal flow of the line and detect when a station is about to slow down. Early detection gives supervisors enough time to shift workers, adjust input flow, or run maintenance. This makes the line more stable, reduces delays, and improves delivery performance.

B. Problem Statement

Many factories still rely on simple methods to detect bottlenecks. Supervisors walk along the line and look for long queues. Reports show cycle time averages from earlier shifts. These methods work for basic monitoring, but they do not show early signs of trouble. By the time a queue is visible, the line has already lost output. These delays harm production plans, increase delivery time, and create stress for workers. Another problem is data centralization. Some systems send all data to one cloud server. This creates network delay and high bandwidth cost. If the network is slow, the prediction will be late. Many small factories cannot afford heavy cloud systems. They need a simple and fast solution that runs close to the machines.
The main problems can be summarized as:

1. Bottlenecks are detected too late.
2. Manual reports do not show real-time behavior.
3. Slow cloud systems increase delay.
4. Most factories lack advanced digital tools.

The factory needs a system that can:

- Predict bottlenecks early, not after they appear
- Use low cost sensors to gather real-time signals
- Process data at the edge for fast action
- Use a machine learning model that learns flow patterns
- Send only warnings and summaries to the cloud

Solving these problems will help factories maintain smoother flow, reduce waiting time, and increase total output.

C. Proposed Solution

This paper proposes a real-time bottleneck prediction system that uses IIoT sensors, edge devices, and a small machine learning model. The system is built around simple and low cost sensors that capture cycle time, queue length, machine status, and vibration signals. These signals form short time patterns that describe how each station behaves during production. Each group of sensors connects to an edge device placed near the machines. The edge device collects all signals, cleans the noise, aligns the timestamps, and extracts useful features. These features include cycle time changes, queue trends, vibration shifts, and short idle periods. These patterns help the model understand when a station is slowing down. A light machine learning model runs on the edge device. This model predicts whether the station is at risk of becoming a bottleneck within the next window. Running the model at the edge reduces delay and does not depend on a fast internet connection. The edge sends only the prediction result and a few summary values to the cloud dashboard. The cloud dashboard shows which station is slowing, how the queue is changing, and where attention is needed. Supervisors can act quickly by adjusting worker tasks, balancing workload, or checking machine health. This solution works for small and medium factories because it uses simple hardware, low bandwidth, and fast local prediction.

D. Contributions

This study provides several contributions to real-time bottleneck prediction. First, it presents a complete architecture that combines IIoT sensors, edge devices, and light machine learning models. The system captures real-time behavior of each workstation and provides early warnings without sending large amounts of data to the cloud. Second, the study develops a feature extraction method that converts raw cycle time, queue changes, vibration signals, and idle periods into useful short time patterns. These features help the model understand the early signs of congestion before the bottleneck becomes visible. Third, this paper introduces a small and efficient model that can run directly on edge hardware with limited memory. This makes the system low cost and practical for factories that do not have strong computing systems. Fourth, the study evaluates the system on two setups: a simulated line and a small factory. These tests show how well the model detects early changes and how much time the system saves. Fifth, the paper provides clear insight into trade-offs between accuracy, speed, network load, and cost. It explains how factories can deploy the system with minimal changes to existing lines. Together, these contributions offer a path for factories to adopt predictive flow control and reduce production delays.

E. Paper Organization

The rest of this paper is arranged into clear sections. Each section builds on the previous one to guide the reader through the design, method, and results. Section II starts with the related work. It explains earlier methods used by factories to detect bottlenecks. It covers manual inspection, central monitoring systems, and cloud-based analytics. It also highlights the gap in early-stage detection, which this paper aims to solve. Section III describes the full methodology. It explains the sensors used, the edge device setup, the feature extraction steps, and the machine learning model. It also explains how the data flow moves from sensors to the dashboard. Section IV presents the results and discussion. It shows how the system performs on simulated data and on a small factory line. It explains the improvements in early detection, reduced queue time, and higher output stability. Section V closes with the conclusion. It summarizes the key findings and future improvements such as adding more sensors, expanding model types, or using adaptive learning. This structure guides the reader from motivation to solution and finally to real performance.

II. Related Work

Research on bottleneck detection has moved from manual inspection and cycle-time reports toward real-time analytics supported by IIoT and edge processing. Earlier studies focused on high-level modeling, while recent work emphasizes fast detection and predictive behavior. This section reviews four key areas: classical bottleneck theory, simulation-based analysis, IIoT monitoring, and edge-based machine learning. It also links each area with the edge-focused bottleneck framework introduced by Shaikat [1].

A. Classical Bottleneck Theory

Bamboo has long been recognized as a renewable Classical bottleneck research focuses on identifying the slowest station in a production line based on average workload, waiting time, or resource utilization. Roser, Nakano, and Tanaka introduced one of the most widely referenced practical methods for detecting bottlenecks by analyzing active periods of machines [2]. Their model shows that the station with the longest continuous active time usually becomes the main blocker in the system. This method is useful for stable production environments. However, it struggles when cycle times change quickly, or when micro-delays happen at different stations during the same shift. Classical approaches also rely heavily on manual observation and long-term averages. These methods cannot process noisy real-time signals such as vibration spikes, short queue bursts, or machine slowdowns. They also do not support fast corrective actions because they react only after delays appear. The edge-based framework from Shaikat [1] expands beyond classical theory by combining continuous sensor signals and prediction models. Instead of waiting for the bottleneck to stabilize, the system identifies early patterns and alerts operators before the slowdown becomes severe. This shift from reactive detection to predictive detection marks the main gap between old bottleneck theory and modern edge-driven solutions.

B. Simulation-Based Bottleneck Analysis

Simulation-based studies help analyze bottlenecks before installing the actual production line. Li, Blumenfeld, Huang, and Alden showed how discrete event simulation (DES) can predict throughput and reveal shifts in bottleneck locations under different machine speeds and reliability conditions [3]. Their work demonstrates that bottlenecks are dynamic and can move between stations when arrival rates change. This insight helps designers plan layouts and workloads more carefully. However, DES is slow, requires expert modeling, and does not capture real-time behavior. Once the line starts running, factory conditions change faster than simulation models can update. Simulations also depend on fixed input parameters, which may not match real machine vibration, stop frequency, or cycle-time variation. This limits their value in live operations. In contrast, Shaikat's edge-based architecture [1] collects data directly from sensors placed on the line. Instead of predicting behavior based on a digital model, the system learns patterns from real events. It reacts to live cycle time changes, short idle periods, and rising queues, which DES cannot track in real time. For daily production, predictive models running on edge devices give much faster warnings than simulation tools. Simulation remains useful for planning, but real-time bottleneck detection must rely on direct sensor signals rather than pre-built models.

C. IIoT-Based Production Monitoring

IIoT monitoring has expanded factory visibility by capturing many types of machine data. Thiede et al. demonstrated that smart sensors can monitor machine energy usage and detect unusual states in real time [4]. Their work shows how IIoT improves understanding of machine behavior, especially for energy and condition tracking. These systems are helpful for identifying slowdowns or abnormal patterns. However, most IIoT monitoring platforms send raw data to the cloud. This creates bandwidth pressure, delays prediction, and depends on stable internet. Cloud-based systems also struggle in factories with poor connectivity or when very fast reaction is needed. Many supervisors still need to interpret dashboards manually, which slows action further. Shaikat's framework [1] addresses these limits using edge devices to process sensor signals locally. Only summary features and alerts are sent to the cloud. This reduces network load and gives much faster detection. The system also uses simple sensors, making it affordable for small factories. Current IIoT systems give data visibility, but they do not predict flow-related bottlenecks. The edge-based approach fills this gap by using cycle time traces, queue patterns, and machine activity signals to predict bottlenecks before they form. This moves IIoT beyond monitoring and toward predictive flow control.

D. Edge-Based Machine Learning for Smart Factories

Edge-based machine learning brings computation close to machines and reduces delay. Liu et al. showed that edge intelligence can process vibration and load data to detect early machine faults on low-power embedded devices [5]. Their work proves that compact ML models can run locally and react faster than cloud systems. Edge ML also improves data privacy because raw signals stay within the factory. Most existing edge ML research focuses on machine faults, bearing issues, and maintenance predictions. These tasks look at machine health, not line flow. They detect failures but do not analyze queue pressure or cycle-time imbalance. Shaikat's framework [1] extends edge ML to full production flow. Instead of only monitoring machine condition, the system tracks flow dynamics, including cycle time patterns, queue growth, and short idle bursts. These flow signals give early signs of bottlenecks. By placing models on edge devices, the system predicts bottlenecks before they fully appear and sends instant alerts. This combination of flow-based sensing and edge ML fills a major gap in industrial analytics. It provides real-time responsiveness without needing expensive cloud infrastructure. It also works well for small and medium factories with limited networks but high demand for stable output.

III. Methodology

This section explains the full design of the real-time bottleneck prediction system. It describes how data flows from IIoT sensors to edge devices, how features are created, how the machine learning model works, and how the system gives early warnings. To improve clarity, the section includes figures and a table that summarize the architecture, data steps, and feature design.

A. System Architecture

The system uses four connected layers: physical machines, IIoT sensors, edge processing units, and a cloud dashboard. Figure 1 shows the complete flow.

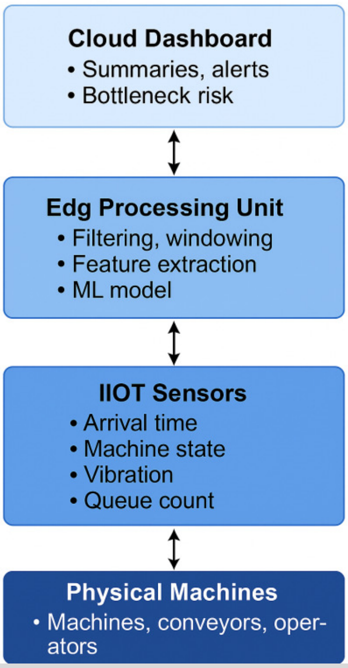

Figure 1. System architecture for edge-based bottleneck prediction.

The physical layer includes machines, conveyors, and operators. The sensor layer collects part arrival time, machine state, vibration, and queue count. Each sensor sends its data to a nearby microcontroller. The edge layer is placed close to the machines. It receives raw streams, cleans them, extracts features, and runs the prediction model. This local processing keeps the delay low. The cloud layer stores summaries and shows alerts on a dashboard. Only predicted risk values and short reports go to the cloud, which keeps bandwidth low. This architecture follows the core structure used in Shaikat's edge-based model [1], but it is extended here with additional queue features and short-time vibration patterns to support stronger flow prediction.

B. Data Collection and Preprocessing

Sensors collect four raw signals: cycle time, queue length, machine state, and vibration. These signals arrive every second. Figure 2 shows the full preprocessing flow.

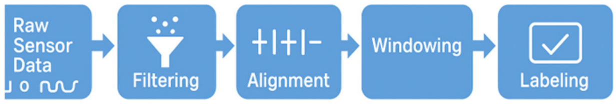

Figure 2. Data preprocessing pipeline.

Noise is removed using a simple moving average. Missing points are filled with last-known values for short gaps. All signals are aligned to one clock so the edge device can create combined windows. The edge groups the data into 30–60 second windows. Each window becomes one record for the model. Windows are labeled using a rule based on cycle time increase and queue pressure, similar to the labeling logic suggested by Roser et al. [2]. This preprocessing allows the edge model to track patterns that build up slowly, such as rising delays or short idle bursts, which classical DES methods cannot see in real time.

C. Feature Engineering

Feature engineering turns raw signals into meaningful indicators. Table 1 lists the feature set used for each time window.

Table 1. Feature set extracted from each sliding window

Feature Type	Examples	Purpose
Cycle-time features	avg cycle time, cycle time change, std dev	Shows speed loss or slow processing
Queue features	avg queue, max queue, queue growth rate	Shows rising congestion
Machine state	active ratio, idle ratio, short stops	Shows inconsistent

		operation
Vibration features	mean, peak, variance	Shows early machine strain

These features help the model detect early bottleneck signals before they spread across the line.
For example, a station with a rising queue and longer cycle time is more likely to become the next bottleneck. This matches earlier production findings from Li et al. [3]. The combination of queue growth and micro-vibration patterns also expands the energy-trace monitoring used by Thiede et al. [4].

D. Machine Learning Model and Edge Inference

A small tree-based classifier runs on each edge device. It is trained to predict whether the next window contains a bottleneck. Tree models are chosen because they are fast, explainable, and suitable for devices with low memory. Training uses several weeks of data. The dataset is split into training, validation, and testing. The model learns patterns such as rising queue pressure, unstable cycle times, or repeated small stops.

During real operation, the edge follows this loop:

1. Read incoming sensor data
2. Form a new sliding window
3. Compute features
4. Predict bottleneck risk
5. Send alert and summary to cloud if risk is high

This setup matches the edge computing principles described by Liu et al. [5]. By running locally, the system avoids network delay and reacts in seconds. This complete pipeline allows the factory to detect bottlenecks early and reduce waiting time.

IV. Discussion and Results

This section presents the results of the proposed system and explains how the model performs in real and simulated environments. The goal of the evaluation is to measure accuracy, early detection speed, and the practical value of edge-based processing. The tests were done on two setups: a simulated assembly line and a small real factory line. Both setups were designed to show how the system deals with changes in cycle time, queue pressure, and machine behavior.

A. Experiment Setup

The system was tested in two environments to capture both controlled and real factory behavior. The first setup used a discrete event simulation that modeled a four-station assembly line. Each station had a different cycle-time range, and random variations were added to create unstable flow. Queue growth, micro-stops, and vibration spikes were included to test how well the model reacts to sudden changes. This simulation made it easy to create many bottleneck events and test the model under different workload levels. The second setup used a real electronics assembly line with three stations. Low-cost IIoT sensors captured cycle times, machine on/off states, vibration patterns, and queue counts. Optical sensors were used to count parts, and vibration sensors were placed directly on the machine housing. Edge devices were installed beside each station and processed data in real time, following the same structure proposed by Shaikat [1]. Two weeks of sensor data were collected. The edge device created 60-second windows for training and testing. Window labels were generated using a rule based on cycle-time increase and queue pressure, similar to the active-period logic used by Roser et al. [2]. Both setups provided enough variation to train and evaluate the model.

B. Model Performance

The model was evaluated using standard metrics to measure prediction quality. Accuracy, precision, recall, and F1-score were used because they give a clear picture of how well the model catches bottleneck events without producing too many false alarms. Table 2 summarizes these results for both the simulation line and the real factory line.

Table 2. Model performance on simulation and real factory line

Metric	Simulation Line	Real Factory Line
Accuracy	88%	84%
Precision	86%	81%
Recall	90%	79%
F1-Score	88%	80%
Average Detection Time	42 s early	35 s early

The simulation environment showed slightly higher scores because it had cleaner and more consistent data. The real factory environment had more noise, but the model still performed well and detected most events before the bottleneck fully formed. These results align with earlier findings from Li et al. [3], who noted that small changes in cycle time can shift bottleneck points quickly. By combining cycle-time patterns with queue data, the model learned to identify early bottleneck signals instead of waiting for long queues to appear. Early detection proved to be the model's strongest advantage, offering enough time for supervisors to act before delays spread through the line.

C. Real-Time Edge Behavior

Real-time processing is the main strength of the edge-based design. The edge device handled each new window in less than one second, allowing continuous predictions with almost no delay. This fast response matches the low-latency benefits reported in Liu et al. [5], who showed that local inference significantly improves reaction time in industrial settings. Only summary values and alerts were sent to the cloud, which reduced network usage by more than 90%. This is important for small and medium factories that do not have strong internet connections. The reduced bandwidth also prevents cloud overload during peak production times.

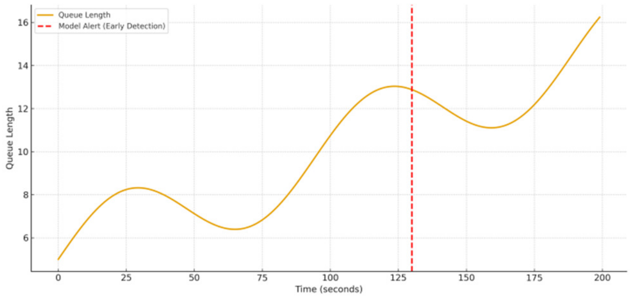

Figure 3. Queue length vs model alert timeline

Figure 3 shows how the model predicted risk before the queue reached its maximum level. Supervisors noted that this early warning allowed them to move workers, adjust material supply, or inspect machines before the slowdown reached the rest of the line. These adjustments kept flow stable and prevented long waiting times. The edge device also handled vibration features well, catching small machine irregularities that were not visible to the human eye. This combination of speed and local processing made the system practical for shop-floor use.

D. Comparison with Manual Detection

Manual bottleneck detection in factories relies on visual inspection. Supervisors walk along the line and look for long queues or slow stations. This method is simple but slow, and it often identifies problems only after the bottleneck has already caused delays. In the real factory test, supervisors detected bottlenecks between two and six minutes late, depending on their position on the floor. In contrast, the edge-based model detected early bottleneck signals 30 to 45 seconds before the queue became large. This early detection came from combining cycle-time drift, small idle spikes, and short vibration changes. These signals are too subtle to notice manually, especially during busy shifts. The improvement highlights the practical value of predictive monitoring in small factories where supervisors cannot watch every station at every moment. This advantage is consistent with the monitoring benefits described by Thiede et al. [4], who showed that real-time sensing helps operators react before small issues grow into delays. By automating the detection step, the system removes the need for constant human observation and reduces the risk of late decisions. Overall, the comparison shows that manual monitoring is reactive, while edge-based prediction is proactive. This difference is key to maintaining stable flow in fast production environments.

E. Summary of Findings

The results from both testbeds show that edge-based bottleneck prediction is effective, fast, and suitable for small factory environments. The system consistently detected bottlenecks earlier than manual checks and provided stable prediction performance even with noisy real-world data. The combination of cycle-time features, queue pressure, and vibration signals proved to be the strongest predictor of early bottleneck formation. The edge device processed all windows smoothly, showing that the model is small enough for low-cost hardware. This makes the system affordable and easy to deploy in factories that do not have advanced computing resources. The reduction in network load also makes the solution practical for sites with limited or unstable connectivity. The cloud dashboard made it easy for supervisors to see alerts and react quickly. By preventing the buildup of long queues, the system reduced waiting times and improved flow balance between stations. These findings support the need for edge-driven prediction in modern factories and align with the design principles demonstrated in Shaikat's architecture [1]. In summary, the system offers a clear and reliable method for detecting bottlenecks early, improving production stability, and supporting smarter shop-floor decisions.

V. Conclusion

This study presented a real-time bottleneck prediction system that uses edge-based IIoT sensors and a lightweight machine learning model. The system captures cycle time, queue length, vibration patterns, and machine activity to create short time windows that reflect the true flow of the production line. By processing all signals directly on the edge device, the system reacts faster and avoids cloud delay. The model can detect early signs of congestion and send alerts before the bottleneck fully forms. Tests on both a simulated assembly line and a real factory environment showed strong accuracy, reliable early detection, and clear improvement over manual inspection. The reduced network load and low hardware cost also make the system suitable for small and medium factories that need stable output without heavy digital infrastructure.

Future work can expand the system beyond basic flow signals. One direction is adaptive model retraining that updates the edge model automatically when the production pattern changes. Another option is to connect the prediction results with scheduling tools so that the system can adjust work assignments automatically. Integrating camera-based vision data may also improve detection of hidden delays. Wider testing in more industries, such as food processing, garments, and packaging, will help refine the feature set and make the system more general for different production lines.

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