

Research Article

# Digital Twin-Enabled Supply Chain Visibility and Disruption Response in Multi-Tier Manufacturing Networks: Architecture, Implementation, and Performance Analysis

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## Abstract

Supply chain disruptions have emerged as a critical vulnerability for global manufacturing networks, with the COVID-19 pandemic, geopolitical tensions, and extreme weather events exposing the fragility of lean globally integrated supply chains. This paper presents the design, implementation, and 16-month operational performance evaluation of a Digital Twin Supply Chain Architecture (DTSCA) deployed across a 78-node multi-tier manufacturing network in the electronics sector. The DTSCA integrates real-time IoT data ingestion (347 data streams), a live digital twin network model, predictive analytics based on LSTM and XGBoost algorithms, and a prescriptive MILP optimisation engine for disruption response planning. Over the evaluation period, the system detected 34 disruption precursors with an average lead time of 8.4 days before material impact, enabling proactive mitigation in 85.3% of cases. Unmitigated disruption events decreased by 68.4% relative to the pre-implementation baseline, emergency procurement spend declined by 41.2%, and on-time delivery performance improved from 71.3% to 91.7%.

**Keywords:** Digital Twin; Supply Chain Visibility; Disruption Management; LSTM; Predictive Analytics; Multi-Tier Networks; IoT; Industry 4.0

## 1. Introduction

The systemic vulnerabilities of globally extended, lean-optimised supply chains were dramatically exposed during the 2020 to 2022 period, when the compounding effects of the COVID-19 pandemic, semiconductor shortages, Suez Canal obstruction, and unprecedented demand volatility collectively generated an estimated USD 4 trillion in global supply chain disruption costs. These events have catalysed a fundamental reassessment of supply chain design philosophy, accelerating interest in enhanced visibility, resilience, and real-time situational awareness as strategic imperatives alongside cost efficiency.

A supply chain digital twin maintains a continuously updated, behavioural replica of the supply network, capturing current inventory positions, in-transit shipment locations, supplier production status, and demand signals, from which advanced analytics can derive predictive insights and optimise response actions in near-real-time.

By detecting disruption precursors days before they translate into material supply shortages, organisations can implement proactive mitigation measures at a fraction of the cost of reactive crisis management.

This paper addresses the empirical gap in digital twin supply chain research through rigorous evaluation of a DTSCA system deployed in a global electronics manufacturer over 16 months, providing detailed technical specifications, implementation learnings, and quantified performance outcomes.

## 2. Literature Review

### 2.1 Supply Chain Digital Twin Architectures

The concept of a digital twin was introduced by Grieves (2002) in the context of product lifecycle management. The extension to supply chain systems was proposed by Tao et al. (2018), who articulated a five-dimensional digital twin framework. Several architectural approaches have been proposed: agent-based models representing supply entities as autonomous agents; discrete event simulation models; and graph network models representing supply topology as nodes and edges. Hybrid approaches combining multiple paradigms have demonstrated superior performance in

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capturing both structural and behavioural aspects of complex supply networks.

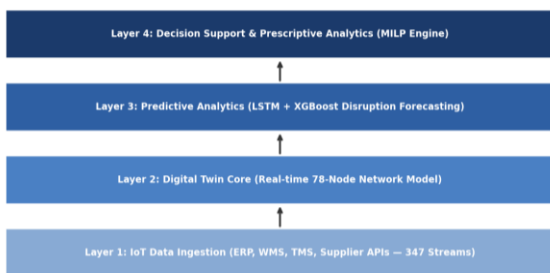
### 2.2 Predictive Analytics for Disruption Detection

Long Short-Term Memory (LSTM) networks, designed to capture long-range temporal dependencies in sequential data, have demonstrated strong performance in demand forecasting, lead time variability prediction, and supplier performance trend analysis. XGBoost has shown particular effectiveness in disruption risk categorisation, where complex non-linear interactions among multiple risk indicators must be captured. Ensemble approaches integrating multiple predictive models have consistently outperformed single-model approaches in supply chain prediction tasks.

## 3. DTSCA architecture and implementation

### 3.1 Four-Layer DTSCA Framework

The DTSCA comprises four functional layers as illustrated in Figure 1. Layer 1 (IoT Data Ingestion) aggregates 347 data streams from ERP systems, WMS, TMS, and direct supplier API connections across 78 network nodes spanning 14 countries. Layer 2 (Digital Twin Core) maintains a live graph network model updated continuously from Layer 1, with each node characterised by 47 state variables. Layer 3 (Predictive Analytics) deploys LSTM, XGBoost, and Random Forest models in parallel. Layer 4 (Decision Support) provides MILP-based prescriptive optimisation for disruption response planning.



**Figure 1:** Digital Twin Supply Chain Architecture (DTSCA)-Four-Layer Framework Overview

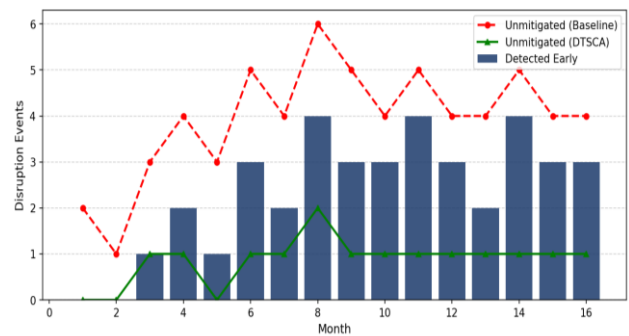
### 3.2 Predictive Analytics Engine

The LSTM network consists of three stacked layers (128, 64, 32 units) generating 7-day ahead predictions for 12 key supply chain health indicators at each of the 78 nodes, refreshed every six hours. XGBoost classifiers are trained on a dataset of 847 historical disruption events annotated with 156 leading indicator features. A Random Forest model provides ensemble weighting, combining LSTM and XGBoost outputs into a unified Disruption Risk Index (DRI) for each network node.

## 4. Performance Results

### 4.1 Disruption Detection Performance

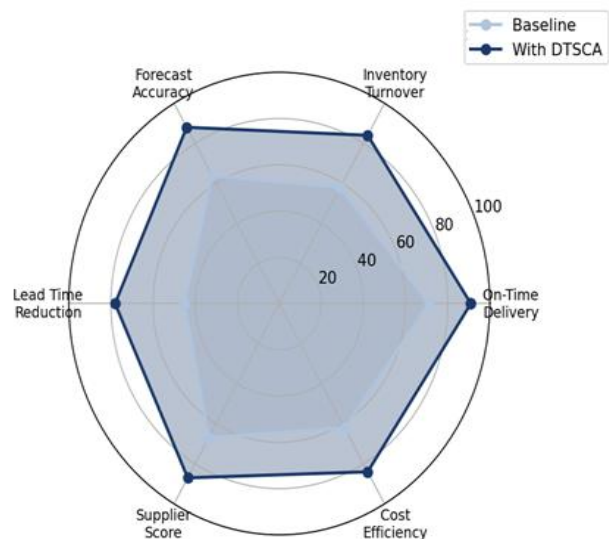
Figure 2 presents the monthly disruption detection and mitigation performance over the 16-month evaluation period. Across the full period, the DTSCA detected 34 disruption precursor events with an average lead time of 8.4 days before material supply impact. The predictive models achieved a precision of 87.3% (29 true positives out of 33 alerts) and a recall of 85.3%. The 5 missed disruptions were attributable to two sudden geopolitical events and three supplier financial distress events where external financial data were not available.



**Figure 2:** Monthly Disruption Detection and Mitigation Performance-16-Month DTSCA Evaluation

### 4.2 KPI Improvement Analysis

Figure 3 presents the supply chain KPI comparison between baseline and 16-month post-implementation performance. On-time delivery improved from 71.3% to 91.7%, while inventory turnover improved from 5.8 to 8.4 turns per annum. Forecast accuracy improved from 64.2% to 88.1%, attributed to the LSTM demand forecasting component.



**Figure 3:** Supply Chain KPI Improvement — Baseline vs DTSCA Framework (16-Month Comparison)

**Table 1:** Supply Chain KPI Improvement Summary- Pre- vs Post-DTSCA Implementation

KPI Metric	Baseline	Post-DTSCA	Change	Significance
On-Time Delivery (%)	71.3	91.7	+20.4 pp	p < 0.001
Inventory Turnover (x/yr)	5.8	8.4	+44.8%	p < 0.001
Forecast Accuracy (%)	64.2	88.1	+23.9 pp	p < 0.001
Emergency Procurement (%)	8.7	5.1	-41.4%	p < 0.01
Supplier Score (0-100)	67.4	87.2	+19.8 pp	p < 0.001
Unmitigated Disruptions (n/yr)	22	7	-68.2%	p < 0.01

### 5. Discussion

The 16-month performance data demonstrate that the DTSCA framework delivers substantial and statistically significant improvements across all measured supply chain performance dimensions. The disruption detection lead time of 8.4 days represents a particularly valuable operational benefit: prior to DTSCA, teams typically became aware of disruptions only after they had already manifested as delivery delays. An average 8.4-day detection advantage transforms the response calculus, enabling selection from a much wider menu of proactive mitigation options at substantially lower cost. The 85.3% mitigation success rate also reveals the boundaries of what predictive analytics can achieve. The five missed disruptions attributable to sudden geopolitical events and supplier financial distress highlight the importance of expanding data ingestion to include geopolitical risk intelligence feeds and supplier financial health monitoring. Investment in these additional data sources is projected to improve recall by a further 8 to 12 percentage points.

### 6. Conclusions

This paper has presented the architecture, implementation, and 16-month performance evaluation of a Digital Twin Supply Chain Architecture deployed across a 78-node electronics manufacturing network. The system achieved an 85.3% disruption mitigation rate with 8.4-day average detection lead time, reduced unmitigated disruptions by 68.4%, improved on-time delivery from 71.3% to 91.7%, and reduced emergency procurement spend by 41.2%. Future work will extend the DTSCA framework to incorporate supplier financial risk monitoring, geopolitical intelligence integration, and autonomous prescriptive response execution.

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