Predictive Demand Disruption Signals for Supply Chain Networks

Yinzhu Quan, Ashwin S. Pothen, Yao Xie, and Benoit Montreuil
Physical Internet Center, Supply Chain and Logistics Institute
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology, Atlanta, U.S.A.
Corresponding author: yquan9@gatech.edu

Abstract: *Supply chain networks today are complex networks with various actors spread across the globe. They operate in a volatile, uncertain, and disruption-prone environment which requires them to perceive, react, and respond proactively to effectively manage their operations and maintain customer satisfaction. In this paper, we introduce a signaling methodology to generate early warning signals for a time series upon deviation from the normal pattern, serving as complementary information to demand forecasts. The methodology can be used to detect deviations in the demand curves, which will be propagated through the network to enable the decision makers in taking prompt actions to minimize the effect of the deviation, and better position the supply chain in the wake of disruptions. Relying just on demand forecasts for decision-making can be detrimental as occasionally demand forecasts are unable to capture sudden discrete changes (step up or down) or a turning point (e.g., change from a decreasing time trend to an increasing trend) accurately and rapidly. In such situations, demand disruption signals with characteristics that complement the behavior of demand forecasts play an essential role in proactively assessing and preparing to navigate the disruptions. The developed demand disruption signals leverage bias-identification tracking signals on demand forecasts to proactively detect demand disruption potentiality. Through real-world industrial experiments, our model significantly outperforms typical disruption detection models and are able to capture changes in demand patterns.*

Keywords: *Physical Internet, Supply Chain Networks, Early Warning Signals, Demand Disruption Signals, Tracking Signals*

1 Introduction

There are numerous disturbances in the highly sophisticated supply chain networks of today that call us to perceive, recognize, react, and respond proactively. Demand disruption signals are early warning indicators that detect deviations in demand patterns from the expected norm, enabling proactive measures to mitigate potential disruptions. These signals serve as complementary information to traditional demand forecasts, providing an additional layer of insight that helps in anticipating and managing unexpected changes in demand. Demand forecasting may occasionally fall short of fully capturing all these demand disturbances, particularly in the volatile, uncertain, complex, and ambiguous (VUCA) world of supply chain networks. Therefore, developing predictive disruption signaling methodologies becomes necessary. Demand disruption signals are very useful tools to make up for the insufficient performance of demand forecasts, avoiding out-of-stock situations, aligning multiple suppliers to ensure timely inventory availability, and making supply chain networks more resilient.

At the end of 2019, COVID-19 broke out worldwide, affecting people's lives and even claiming many of them. In addition to having a high fatality rate, COVID-19 severely disrupted global supply chain networks (Choudhury et al., 2022). It simultaneously interrupts the supply or demand for certainty, stability, availability, visibility, and persistence in the supply chain (Sodhi & Tang, 2021). Along with many instabilities due to the outbreak of COVID-19, forecasts are limited in their ability to capture all these disruptions. If there are early warning signals to inform humans of some disturbances in advance, people can prepare for the disruptions in their early phases and minimize the damage caused by the epidemic. These signals play crucial roles in sensing and predicting unexpected shifts in demand, thereby alerting decision-makers to potential upcoming disruptions.

Enabling to identify rising variability between past and present patterns becomes a crucial technique in our fast-growing supply environment. The capability to respond to supply chain disruptions is enhanced with the use of state-of-the-art supply chain risk tools, such as control tower systems (Lund et al., 2020), which enable end-to-end monitoring, tracking, and transparency. The introduction of the Physical Internet (Montreuil et al., 2013) concept, with its focus on creating an interconnected and resilient global logistics system, further underscores the importance of agility and adaptability in today's supply chain networks. In order to make supply chain networks more resilient, sensitive, agile, and intelligent, most of the current research focuses on the improvement of the demand side (Malmstedt & Bäckstrand, 2022), i.e., how to enhance demand forecasting. However, professional and practical contributions to the enhancement of the supply side are not enough. Therefore, the purpose of this paper is to perceive disruptions in early stages and enable decision-making agents to take prompt actions in advance to reduce the impact of turbulence.

This paper is structured as follows: Section 2 provides the review of existing literature on demand forecasting and signaling methodologies; Section 3 outlines our proposed methodology for generating, filtering, and validating demand disruption signals; Section 4 highlights the performance of our signaling methodology for a real-world e-commerce-based manufacturing firm operating in a highly uncertain and volatile environment; and Section 5 provides concluding remarks and avenues for future research.

2 Related Work

In the current volatile and uncertain world we live in, reliable and fast-evolving prediction has become the main theme in supply chain networks. It is crucial to have predictive capability in manufacturing processes, quality, management, inefficiencies, and even inside manufacturing systems (Choudhary et al., 2009). There are lots of statistical methods and machine learning approaches implemented for predictive analytics (demand forecasting), such as the neural network and Fourier transform (Saito & Kakemoto, 2004), SARIMA (Liu et al., 2001), and Holt-Winters Exponential Smoothing (Hasin et al., 2011), which are widely used in industry.

Most of these methodologies are solely dependent on historical data, which is not well correlated with exogenous events, including economic downturns and upturns, advertising and competing activities, the development of consumer social media use, and interruptions brought on by natural catastrophes (Byrne, 2012). These exogenous events affect the demand realization, leading to the emergence of a bias in the demand forecasts, which should be identified and signaled to the decision-makers of the supply chain network for proactive preparation and mitigation.

Demand disruption signals, broadly speaking, are data streams that the participants in the supply chain may regularly access (Evrard-Samuel, 2008). Demand disruption signals have sensing capabilities, which could enable a firm to identify a disruption in its early phases (Pattanayak et al., 2023). In addition to previous demand insights that connect with present and future demand, they also offer advanced information on demand, such as future planning and scheduling on demand (Hillman & Hochman, 2007). Researchers have utilized anomaly detection and change point methods for identifying such signals. Ensemble anomaly detection helps prevent supply chain input errors from disrupting the quality of realistic sales and projected supply plans (Glaser et al., 2022). Change point detection algorithms use a binary classifier, which are used to identify pattern changes and release early warning signals in the demand process (Aminikhanghahi & Cook, 2017).

The evolution of tracking signals from Page's (1955) initial concept to their enhancement with Brown's (1959) cumulative sum technique highlights their crucial role in identifying changes in pattern. By comparing the cumulative sum of forecast errors against the Mean Absolute Deviation (MAD), tracking signals serve as a powerful mechanism to promptly detect and alert us to disruptions. Tracking signals are widely used in industry to supervise inventory and sales demand (Gorr & McKay, 2005). These signals are able to automatically and rapidly identify pattern changes, such as step jumps and turning points in product demand. Moreover, tracking signals have also been utilized for automatic update of forecasts when an unexpected structural change is observed in the process (Snyder & Koehler, 2009); validation of the proposed forecasting methods (Saroha et al., 2021); and monitoring of forecast results (Rizki et al., 2021). Overall, the use of tracking signals can lead to more efficient inventory management, better allocation of resources, and improved decision-making in response to changes in product demand. Despite their widespread use, tracking signals for demand disruption signals in supply chains have notable limitations. One significant limitation is that they typically use only one-day ahead forecasts, rather than incorporating multi-day ahead forecasts. In this paper, we employ the tracking signal method to identify demand disruption signals, ensuring that companies can efficiently adjust to market dynamics and maintain a proactive stance in the face of potential disruptions.

Our contributions of this paper are as follows:

- We propose an adaptive tracking signal method to identify demand disruption signals.
- We combine tracking signals estimated from multi-day ahead forecasts rather than utilizing just single previously generated forecast.
- We leverage a real-world supply chain network as a testbed for validation of our method, demonstrating superior performance over traditional disruption identification methods.

3 Proposed Method

In this paper, we propose an Adaptive Tracking Signal method to identify demand disruption signals. The method begins by using tracking signal statistics based on multi-day ahead forecasts to generate modified tracking signals. These modified tracking signals quantify deviations from the interquartile range (IQR) of tracking signal statistics and are used as features in the Adaptive Tracking Signal model. The formula of tracking signal could be seen from equation (1), which is the ratio of cumulative sum of error to mean absolute deviation. Our Adaptive Tracking Signal method is constructed in three pivotal sections. We begin by estimating these tracking signal statistics. Then, we modify them to measure their deviation from the control limits using interquartile range (IQR) method (*Section 3.1*). Afterwards, we use filtering method to select highly deviated data to train the model (*Section 3.2*). Finally, we employ a binary classification model to predict demand disruption signals that reveal structural deviations from expected demand patterns (*Section 3.3*). Definitions of the notations used in this paper are listed in Table 1.

$$Tracking\ Signal = \frac{\sum(Actual - Forecast)_t}{Mean\ Absolute\ Deviation} \tag{1}$$

Table 1: Notations and definitions of sets, parameters, and variables

Notation	Definition
$\mathcal{T} = \{1, \dots, T\}$	set of days considered
$\mathcal{H} = \{1,2,3, \dots\}$	set of days ahead forecast considered
d_t	observed demand on day t
a_t	exponentially smoothed demand on day t
$f_{t,\hat{t}}$	demand forecast generated on day $\hat{t}$ for day t
n	length of rolling horizon
$e_{t,h}$	rolling-horizon Mean Absolute Deviation of h-day ahead forecast errors
$s_{t,h}$	tracking signal on day t, based on h-day ahead forecast
$m_{t,h}$	modified tracking signal on day t, based on h-day ahead forecast
b_t	forecast bias using forecast generated on day t

3.1 Estimation of Modified Tracking Signal Based on Multi-Day Ahead Forecasts

We propose modified tracking signal statistics for estimation of demand disruption signals, which quantifies the deviation of the tracking signal statistic from the IQR control limits. These modified tracking signals are used as features in the subsequent classification model. The procedure is described in Algorithm 1. We first compute the tracking signal $s_{t,h}$ based on exponentially smoothed demand data a_t, and then consider a rolling horizon of n periods for estimating the IQR range. The modified tracking signal $m_{t,h}$ is then estimated as the ratio of deviation from IQR to the length of IQR. We estimate $m_{t,h}$ based on multi-day ahead $h \in \mathcal{H}$ forecast generated for a given day $t \in \mathcal{T}$.

In an environment with highly uncertain and volatile demand, demand forecasts are unable to capture the demand accurately. This effect is seen in our experiments from the value of modified tracking signals, but can be used to identify structural changes in demand pattern. When the value of the modified tracking signal is greater than 0, it indicates that the demand data is greater than the demand forecast, implying forecast is underestimating demand. When the value of the modified tracking signal is less than 0, it indicates that the demand data is less than the demand forecast, implying forecast is overestimating demand. A critical observation from our analysis is the gradual transition between overestimating and underestimating demand, marking these periods as pivotal indicators of changes in demand patterns. These modified tracking signals reflect the straight relationship between estimated demand and demand forecast, and will be used as features in the following classification model.

3.2 Implementation of Filtering Method Based on P-Values

We get modified tracking signals, namely features from Section 3.1. In this section, we select data which is highly deviated using filtering method. The reason for the filtering method is that we want to predict significant demand disruption signals. Thus, if demand forecast is good enough, we will not take it into consideration in the model. There are two rules for the filtering method: (1) select increasing signal and decreasing signal (which will be introduced in Section 3.3); (2) select data with p-value smaller than specific threshold. From the perspective of labels, increasing signal and decreasing signal indicate that the forecast falls outside the normal range. On the other hand, p-value assists in data selection by indicating the strength of the relationship between demand and demand forecast, with the selection of threshold adjustable on a case-by-case basis. We choose 0.3 as the threshold in the current case. The combination of two rules makes us select highly deviated data, which will help us train the model. The calculation method of p-value is to compute the percentile of the test residual in the empirical distribution of training residuals. We illustrate the function of the p-value using demand data from 2020, along with a confidence interval based on a 1-day ahead forecast, as shown in Figure 1. In Figure 1, demand data is colored according to the p-value. Data significantly diverging from the prediction, indicating a potential demand disruption signal, yields a very small p-value and is marked in red. An intermediate p-value results in yellow coloring, suggesting a moderate deviation from the forecast. Green indicates that the demand forecast falls within the normal range, associated with a large p-value.

Algorithm 1 Procedure for estimation of modified tracking signal

Input observed demand on day t: d_t, demand forecast generated on day $\hat{t}$ for day t: $f_{t,\hat{t}}$, $\forall t, \hat{t} \in \mathcal{T}$
Output modified tracking signal on day t based on demand forecast generated h-days prior: $m_{t,h}$, $\forall t \in \mathcal{T}, \forall h \in \mathcal{H}$

$t \leftarrow 0$ ▷ initialization
$a_0 \leftarrow d_0$
for $t \in \mathcal{T}$ **do**
  $a_t \leftarrow \alpha * d_t + (1-\alpha) * a_{t-1}$ ▷ demand smoothing parameter (α)
  for $h \in \mathcal{H}$ **do**
    $e_{t,h} \leftarrow \frac{1}{n}\sum_{\tau=t-n}^{t} |a_\tau - f_{\tau,\tau-h}|$ ▷ rolling-horizon Mean Absolute Deviation
    $s_{t,h} \leftarrow \frac{\sum_{\tau=t-n}^{t}(a_\tau - f_{\tau,\tau-h})}{e_{t,h}}$ ▷ tracking signal
    $Q_{1,t}, Q_{3,t} \leftarrow IQR(s_{\tau,h}, \forall \tau \in \{t-m, \ldots, t\})$ ▷ interquartile range
    if $s_{t,h} \geq Q_{3,t}$ **then** $m_{t,h} \leftarrow \frac{s_{t,h}-Q_{3,t}}{Q_{3,t}-Q_{1,t}}$ ▷ modified tracking signal
    else if $s_{t,h} \leq Q_{1,t}$ **then** $m_{t,h} \leftarrow \frac{s_{t,h}-Q_{1,t}}{Q_{3,t}-Q_{1,t}}$
    else $m_{t,h} \leftarrow 0$
    end if
  end for
end for

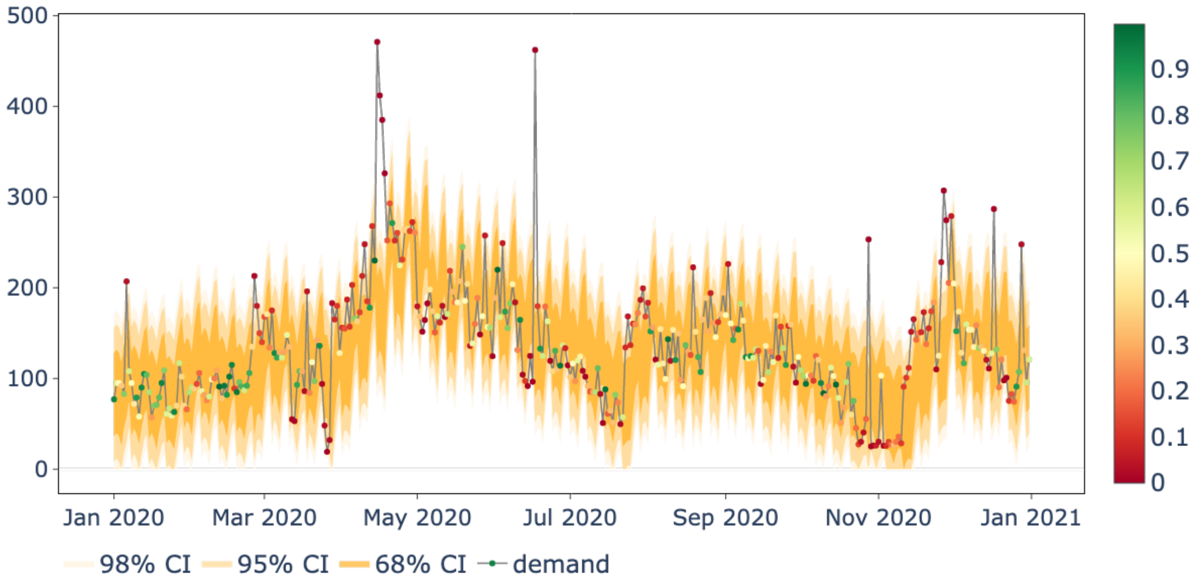

Figure 1: Demand in 2020 with confidence interval using 1-day ahead forecast

3.3 Estimation and Validation of Demand Disruption Signal

In Section 3.1, we focus on deriving features for our model by utilizing modified tracking signals $m_{t,h}$ on day t with h-day ahead forecasts. In Section 3.2, we introduce filtering method to help us select significant data to train the model. In Section 3.3, we aim to estimate the demand disruption signal, implying a structural change in demand pattern, based on the past and present modified tracking signals, as well as multiple days ahead forecasts. For this purpose, we utilize a classification model, Logistic Regression, with demand disruption signal as the dependent variable. Logistic regression is a binary classification algorithm, predicting probabilities using a logistic function. As shown in Equation (2), forecast bias b_t for forecast generated on day t, is defined as the cumulative forecast error in the short term, 14 days for instance. Forecast bias is used to evaluate forecast on day t. We then classify forecast bias using the interquartile range (IQR) method into three categories: negative bias, no bias, and positive bias. A forecast bias above the third quartile is labeled as positive bias, indicating an underestimation of demand; below the first quartile, it is labeled as negative bias, reflecting an overestimation of demand. If the forecast bias falls between these quartiles, it is classified as normal pattern, suggesting that the forecast aligns accurately with actual demand. In our model, forecast biases are directly linked to demand disruption signals. A positive bias combined with demand consistently being greater than demand forecast over the following 14 days signifies an increasing signal, which prompts the need to escalate the forecast. Conversely, a negative bias combined with demand consistently being smaller than demand forecast indicates a decreasing signal, calling for a decrease in the forecast.

$$b_t = \sum_{i=1}^{14}(d_{t+i} - f_{t+i,t}) \quad (2)$$

Figure 2 presents a systematic approach to generating demand disruption signals. The process begins with data collection, comprising six years of demand history from an e-commerce manufacturer, with the initial four years designated for training. The training phase employs a filtering method to select highly disrupted data, preparing for the Logistic Regression model - our chosen tool for its understanding in signaling occurrence confidence. This model is then tested against the subsequent two years of data, which serve as our test dataset. It's important to note that filtering label is excluded during testing to simulate real-world unpredictability. We specifically target data with a p-value less than 0.3, aligning with patterns of significant disruption. The model's effectiveness is gauged through accuracy, precision, and recall metrics. To bring the model online for industrial use, it undergoes daily updates informed by current predictions, parameter adjustments, and label revisions, encapsulated within the red dashed box of Figure 2. This iterative refinement cycle ensures our model continuously adapts to sense and signal demand disruptions effectively.

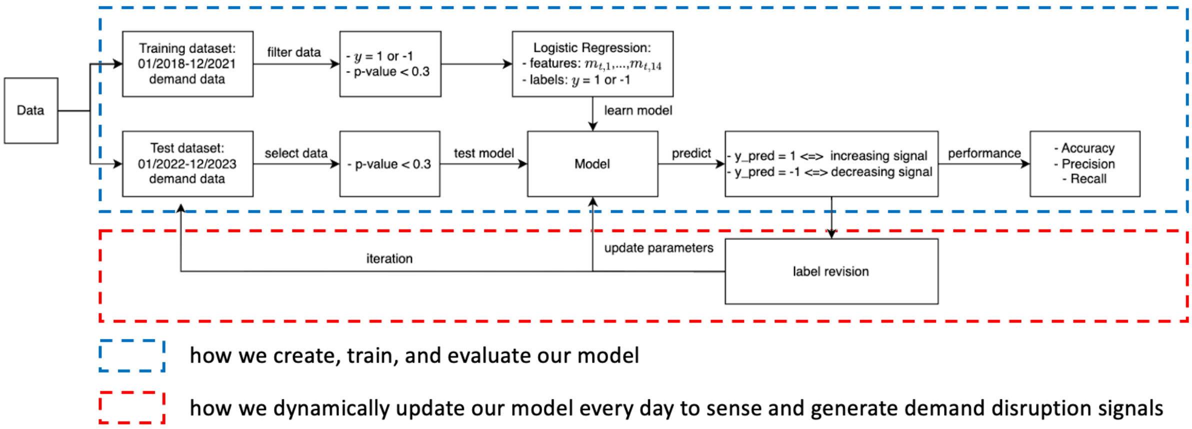

Figure 2: Process of generating demand disruption signals

4 Results

In this section, we show the performance of Adaptive Tracking Signal method in detecting demand disruption signals. In Section 4.1, we evaluate the effectiveness of different signal generation methods. Then, Section 4.2 delves into the sensitivity of our model, analyzing how adjusting the confidence threshold influences the number of detected signals and overall accuracy. Finally, in Section 4.3, we provide practical examples showcasing the detection of increasing demand.

4.1 Results on Validity of Signal Quality

Our study conducts a comprehensive comparison of different signal generation methods applied to master-bedroom bed category from e-commerce-based manufacturing company, focusing on signals with confidence level greater than 75%. We select the rolling horizon of training dataset as 2 weeks, ensuring the model continuously integrates the most recent data and enhancing its responsiveness to changing conditions and trends. The quality of the signals is evaluated against three primary metrics: Accuracy, Precision, and Recall. Accuracy represents the proportion of all signals correctly captured by model; Precision measures the proportion of predicted signals correctly captured by model; and Recall denotes the proportion of true signals correctly captured by model. We validate our model's efficacy using a dataset that encompasses a training phase from January 2018 to December 2021 and a subsequent testing phase from January 2022 to December 2023. Table 2 displays the superior performance of the Adaptive Tracking Signal method, which achieves 77% in Accuracy, 84% in Precision, and 78% in Recall, outperforming the Tracking Signal and Change Point methods in detecting demand disruptions. Adaptive Tracking Signal method outperforms the Tracking Signal and Change Point methods by dynamically adapting to demand patterns, which enhances its ability to accurately capture demand shifts. We use Signal Count to describe the total number of demand disruption signals detected by each method. Missing Value, on the other hand, represents count of signals that the method failed to detect. The similar numbers of missing values across the methods suggest that, while the Adaptive Tracking Signal method detects disruptions more accurately, all methods have comparable sensitivity to when a signal does not appear.

Table 2: Performance of different signal generation methods

Method / Metric	Accuracy	Precision	Recall	Signal Count	Missing Value
Adaptive Tracking Signal	**77%**	**84%**	**78%**	31	14
Tracking Signal	41%	42%	45%	34	11
Change Point	40%	20%	50%	30	15

4.2 Sensitivity Analysis of Signal Confidence Threshold

This subsection examines the impact of the Signal Confidence Threshold on the accuracy and detection count of demand disruption signals. Figure 3 illustrates that as the threshold increases from 50% to 93%, there is a general trend of increasing accuracy, indicating a more selective and precise signal detection. The count of signals declines as the Signal Confidence Threshold rises, indicating more signals are missed. This balance between accuracy and signal count highlights the importance of setting an optimal confidence threshold to maximize the model's effectiveness in identifying true demand disruptions while minimizing missing values.

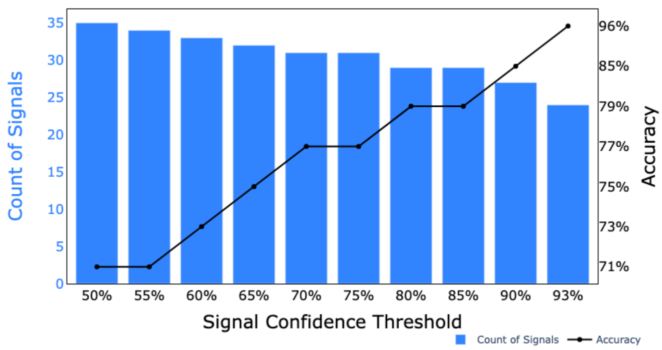

Figure 3: Signal detection and accuracy across different confidence thresholds

4.3 Example of Increasing Demand Disruption Signals

In this section, we use an example of an increasing demand disruption signals to indicate the structural change in demand pattern, where demand forecast is unable to accurately capture the upcoming demand pattern. Figure 4 presents a table of Modified Tracking Signals over a span of days, highlighting a transition in forecasting from overestimating to underestimating, beginning on March 24, 2020, with an 84% confidence level. This shift signifies the model's detection of increasing signals, which grow more accurate over time. Figure 5 visualizes a truly predict increasing demand disruption signal on April 2nd, 2020, highlighting a forecast underestimation for the subsequent, indicating the preparation of out-of-stocks and minimizing lost sales.

	Modified Tracking Signal (based on x-days-ahead forecast)																
Date	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**p-value**	**Signal**	**Confidence**
2020-03-20	-0.29	-0.26	-0.17	-0.08	-0.03	-0.13	-0.19	-0.25	-0.09	0.00	0.00	0.00	0.00	0.00	0.51		
2020-03-21	-0.29	-0.19	-0.10	-0.05	-0.14	-0.20	-0.27	-0.13	0.00	0.00	0.00	0.00	0.00	0.13	0.76		
2020-03-22	-0.21	-0.10	-0.05	-0.15	-0.25	-0.32	-0.14	0.00	0.00	0.00	0.00	0.20	0.32	0.39	0.30		
2020-03-23	-0.11	-0.06	-0.20	-0.30	-0.44	-0.22	0.00	0.00	0.00	0.05	0.47	0.66	0.59	0.60	0.92		
2020-03-24	-0.08	-0.26	-0.37	-0.52	-0.28	0.00	0.00	0.00	0.24	0.78	1.03	1.01	0.82	0.81	0.02	Increasing	84%
2020-03-25	-0.29	-0.43	-0.61	-0.28	0.00	0.00	0.00	0.58	1.09	1.50	1.46	1.33	0.78	0.66	0.03	Increasing	92%
2020-03-26	-0.44	-0.65	-0.21	0.00	0.00	0.39	1.04	1.67	1.94	2.04	1.42	0.88	0.63	0.53	0.00	Increasing	98%
2020-03-27	-0.67	-0.16	0.00	0.14	1.14	1.33	2.14	2.57	2.51	1.44	0.86	0.67	0.51	0.52	0.02	Increasing	100%
2020-03-28	-0.13	0.00	0.39	1.29	1.93	2.25	2.95	2.51	1.37	0.76	0.61	0.50	0.50	0.49	0.03	Increasing	100%
2020-03-29	0.00	0.22	1.12	1.66	2.56	2.47	1.94	1.14	0.68	0.48	0.41	0.45	0.45	0.34	0.09	Increasing	100%
2020-03-30	0.04	0.84	1.36	2.10	1.71	1.28	0.84	0.56	0.43	0.32	0.35	0.38	0.31	0.21	0.12	Increasing	100%
2020-03-31	0.69	1.00	1.45	1.04	0.79	0.63	0.41	0.35	0.28	0.29	0.32	0.28	0.21	0.07	0.46		
2020-04-01	0.84	1.27	0.78	0.56	0.50	0.34	0.27	0.25	0.27	0.28	0.25	0.20	0.08	0.00	0.10	Increasing	98%
2020-04-02	1.53	0.90	0.58	0.47	0.39	0.32	0.24	0.31	0.32	0.22	0.19	0.08	0.04	0.00	0.15	Increasing	97%
2020-04-03	1.31	0.73	0.52	0.37	0.37	0.28	0.30	0.37	0.27	0.17	0.08	0.03	0.04	0.00	0.07	Increasing	96%
2020-04-04	1.08	0.65	0.42	0.36	0.33	0.38	0.41	0.34	0.23	0.07	0.03	0.03	0.04	0.00	0.12	Increasing	95%
2020-04-05	0.84	0.47	0.35	0.32	0.44	0.51	0.38	0.27	0.10	0.04	0.04	0.03	0.03	0.00	0.09	Increasing	94%

Modified Tracking signals

±0	±1	±2	±3

*A tracking statistic denoting **deviation** of today's realized demand from forecast generated x-days ago*

p-value

0.00	0.25	0.50	0.75	1.00

*A tracking statistic denoting **position** of today's realized demand with respect to forecast confidence interval*

0: demand is far outside confidence intervals
1: demand is well within confidence intervals

Figure 4: Illustrative example of structural change in demand pattern

5 Conclusion

In this paper, we introduce a novel method for generating demand disruption signals within supply chain networks, designed to detect deviations in the demand curve. Our Adaptive Tracking Signal approach demonstrates significant improvements over traditional models by effectively capturing and responding to sudden shifts in demand patterns. The real-world application to an e-commerce-based manufacturing firm highlights our method's ability to

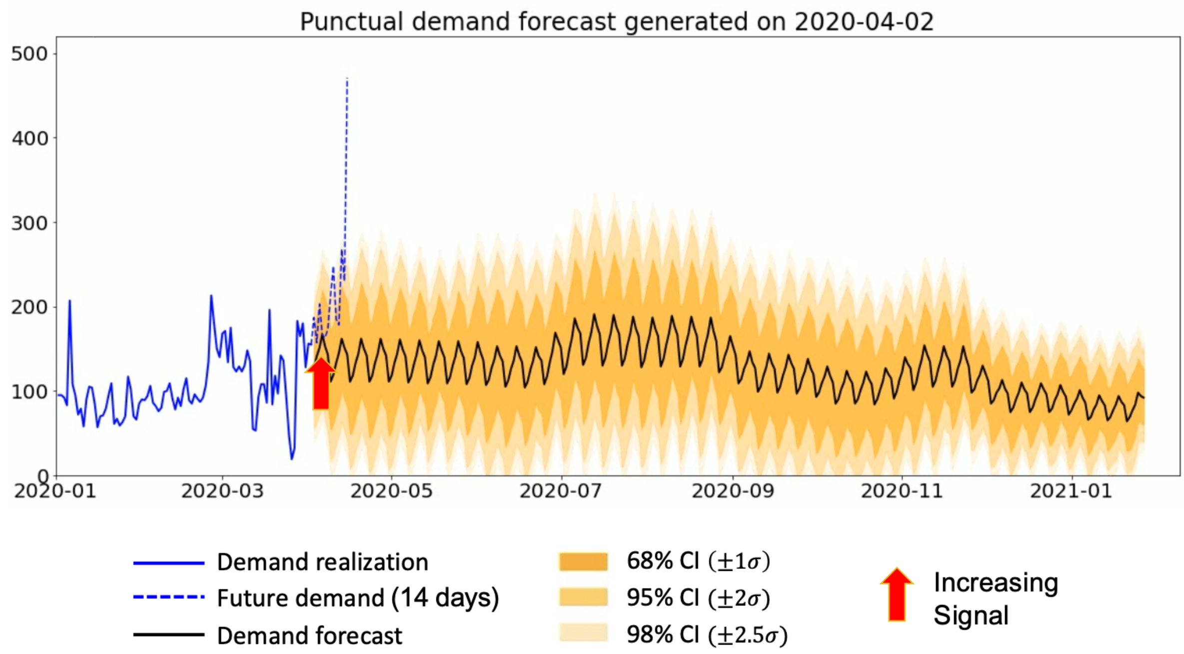

Figure 5: Visualization of an increasing demand disruption signal

proactively identify disruptions, thereby enhancing the resilience and agility of supply chains. By enabling more accurate predictions of demand disruptions, companies can better manage inventory levels, optimize resource allocation, and minimize the impact of supply chain disturbances. This capability is particularly crucial in today's volatile market environments, where conventional forecasting techniques often fall short. Future research could explore the integration of more complex machine learning models, such as neural networks, to develop a more coherent model. Additionally, expanding the scope of our study to include a broader range of industries would further validate the adaptability and effectiveness of our approach across various market dynamics, including supply, transportation, and other critical aspects of supply chains beyond demand.

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