**Research papers:**  
  
<https://link.springer.com/article/10.1186/s40537-020-00329-2> (Predictive big data analytics)

* Aims at reviewing the articles published in demand and sales forecasting in the presence of big data
* To provide a classification of algorithms used in demand forecasting in SCs and its applications in multiple domains
* Most frequently used algos- 1) neural nets 2) Regression 3) Time series(ARIMA) 4) Support vector machines 5) Decision tree
* Time series: forecasting search traffic(service demand) | exponential smoothing to provide short-term, mid-term and long-term demand trends in the chemical industry | for perishable products- ARIMA and Holt-winters
* Clustering analysis(K-means, Self-organizing maps, fuzzy clustering): Bakery chains | Fuel demand forecasting | electrical consumption
* KNN(K-nearest neighbour) : automotive spare parts SC | in Walmart Supply chain planning
* Artificial Neural Networks: predicting demand in Brazilian logistics | spare parts demand | e-logistics demand in China
* Regression Analysis: pharmaceutical industry
* Support vector machines: household and personal care SC, car sales
* Mixed approaches: Clustering + moving average+ Bayesian belief network
* Discusses incorporating driving factors such as economic instability, inflation and purchasing power to improve the quality of forecasts.
* Discusses closed loop SCs( inclusion of recycling, remanufacturing and refurbishment)
* **Key find**: CLSCs deal with a lack of quality data for remanufacturing….as a result, optimal scheduling of remanufacturing is cumbersome.
* One key finding from reviewing the existing literature was that there is a very limited research conducted on the applications of BDA in CLSC and reverse logistics.

<https://www.tandfonline.com/doi/full/10.1080/13675567.2020.1803246> (Machine learning demand forecasting and supply chain performance)

* Supply chain firms suffer from variance amplification due to information distortion and operational inefficiencies
* Prior research suggests that applying advanced demand forecasting such as machine learning can improve the performance of supply chains
* However, they do not discuss the magnitude of savings which this research discusses
* This research uses hybrid demand forecasting methods, i.e. ARIMAX and NNS.
* Previously used methods in the company: Holt-Winters and Damped trend
* ***Hypothesis***: Compared with traditional time-series-based forecasting approaches, ML-based forecasting approaches could significantly improve the efficiency of the supply chain.
* We use the following metrics to evaluate supply chain efficiency: inventory turn (IT = Cost of Goods Sold / Average Inventory), forecast accuracy (FA measured by Mean Absolute Percentage Error) and cash-conversion cycle (CCC = days of outstanding receivable + days of outstanding inventory – days of outstanding payable). The first two are operational–oriented measures while the CCC reflects working capital efficiency and financially oriented barometer
* The ARIMAX (1,1,0), ARIMAX (3,0,0), NN- 7-input->(5-1st hidden layer, 2- 2nd hidden layer)- 1-output
* ARIMAX (1,1,0)-88.9%, ARIMAX (3,0,0) - 89.1%, NN- 89.4%
* Results: Research found significant improvement in supply chain efficiency. The forecasting methods could capture complex relationships of variables contributing to demand and perform better than traditional methods.
* We also found that the ARIMAX technique was better at predicting the peaks in demand, while neural networks generate more ‘smoothed' prediction with better accuracy.
* Statistically significant improvement in 1) operational and financial metrics and 2) Inventory performance( lower storage and facility costs, lower transportation costs) -> improved return on assets and profits.
* Limitations: The findings do not provide any benefits for the fashion and smartphone industries.
* **Major limitation-**> use of a single dataset to evaluate forecasting methods

<https://www.sciencedirect.com/science/article/pii/S0377221706012057?casa_token=v7GEGMHbzSEAAAAA:VL_S9b8L9EmjgVDsmu5gLYHLfbXa96-sJJh2BH1ZA39UwkQXhXDeFVhBEbeVveKYVsFAQbyD6g> (application of ML techniques for supply chain demand forecasting)

* Objectives: to study the feasibility and perform a comparative analysis of forecasting the distorted demand signals in the extended supply chain using non-linear ML techniques
* Focuses on forecasting demand at the upstream end of the Supply chain.
* Value of information sharing across SCs-> important to combat demand signal distortion-> however, gap between the ideal integrated supply chain and reality
* In many SCs- power regimes- prevent SC optimization
* Introduction of inaccurate information into the system-> leads to demand distortion-> case of telecom industry-> some partners were double forecasting and ration gaming->despite having a collaborative system in place.
* Above reasons likely to hinder SC collaboration
* Current reality of business-> extended supply chains not collaborative all the way upstream to the manufacturer and beyond.
* The problem of distorted demand forecasting is important to businesses, especially those upstream end of the SCs
* Distorted demand- data: 1) simulations of an extend supply chain

2) Foundries data provided by statistics canada

-Traditional methods used: Naive, moving average, trend, Linear regression

Advanced methods: Recurrent Neural nets, SVM, NN

Results: 1) Advanced techniques did not provide a large improvement over traditional for simulation data set.

2) For foundries dataset: RNN and SVM provide larger improvements.

3)Did not find ML techniques perform significantly better than linear regression.

4) Overall, use of ML techniques and MLR provide more accurate forecast than traditional.

5) Future: investigating the impact of information sharing on forecast accuracy.

<https://www.sciencedirect.com/science/article/pii/S2212827122004036>

**Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities**