

**DATA-DRIVEN SUPPLY CHAIN FORECASTING AND
INVENTORY OPTIMIZATION: MACHINE LEARNING
BASED MODELS AND METHODOLOGIES**

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DATA-DRIVEN SUPPLY CHAIN FORECASTING AND INVENTORY OPTIMIZATION: MACHINE LEARNING BASED MODELS AND METHODOLOGIES

by

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CERTIFICATE

This is to certify that the thesis entitled “**Data-driven Supply Chain Forecasting and Inventory Optimization: Machine Learning Based Models and Methodologies**” being submitted by Sushil Punia to the Indian Institute of Technology Delhi for the award of the degree of Doctor of Philosophy is a bonafide record of original research work carried out by him. He has worked under our supervision and has fulfilled the requirements for the submission of the thesis, which has reached the requisite standard.

The results contained in this thesis have not been submitted, in part or full, to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

Firms are building their strategies to harness data and use artificial intelligence to manage complex and competitive business environments. The growing availability of large datasets (“big data”) and recent advances in the area of machine learning have led to the increased focus of firms on developing data-driven solutions to the problems in the Operations and Supply Chain Management (OSCM) field. Traditionally, problems of OSCM were largely tackled through mathematical modeling and optimization, and in a few cases, through empirical studies. In recent years, research focuses on using data and data modeling, known as (data) analytics, for solving their business problems. The integration of data analytics and the domain knowledge of OSCM has the potential to derive rules for effective direction and optimization of the operations and supply chain.

In analytics, decision-makers develop data-based models to extrapolate the patterns in historical data to get insights about the future, and then use them into optimization models to obtain an effective solution to the business problems. Deriving the insights about future outcomes is known as *predictive analytics*. Using predictive analytics results in the optimization model to obtain actionable insights is known as *prescriptive analytics*. The predictive analytics and prescriptive analytics are complete within themselves. However, their combined use (called predict-then-optimize) leads to a true data-driven decision support system that can create value.

In this research, predictive and prescriptive analytics models are developed to address various challenges in supply chain forecasting and inventory optimization. This research work addresses the demand (sales) forecasting problem in a complex environment by proposing

big data analytics and machine (and deep) learning based on a Demand Forecasting Model (DFM). The proposed DFM consists of a novel forecasting method that ensembles long-short-term-memory networks and random forest through an evolutionary optimization algorithm. DFM is capable of modeling the model time and covariates-based variations, and thus, it has better accuracy than standalone state-of-the-art forecasting methods. A sample of 4235 demand series with structured and unstructured data (also known as “big data”) is used for the analysis. It has been observed that DFM is suitable to provide accurate forecasts to develop demand plans for operational and tactical decisions.

The research work is further extended by developing a novel Demand Forecasting Decision Model (DFDM) to provide the forecasts for relatively long-term forecasts where big data models are not applicable. The proposed DFDM mathematically integrates judgmental estimates from experts and quantitative forecasts from econometric time-series and machine learning models. Through this work, it has been explored whether the human judgment is still apposite in the era of artificial intelligence, i.e., machine learning.

Further, it is known that the supply chain requires short-term up to long-run aggregated forecasts for making strategic, tactical, and operational decisions. These forecasts need to be accurate and coherent. However, using different predictive analytics methods for short-term up to long-run forecasts in a supply chain leads to incoherency in forecasts at different planning and decision levels. It leads to the misalignment in management and wastage of resources of the organization. Thus, a novel supply chain forecasting framework, a combination of temporal and cross-sectional hierarchical forecasting, is proposed to generate coherent forecasts at all levels of a supply chain. The proposed framework also provides more accurate forecasts than forecasts at different levels of supply chains.

In the final model, predictive analytics is linked to the prescriptive analytics model. A data-driven inventory optimization model is developed. The multi-item inventory optimization problem with limited capacity/budget is solved using the machine learning and optimization model. The mathematical solutions to the newsvendor problem are available in the literature on inventory management. However, these available solutions make several assumptions about demand distributions and other parameters, which are often incorrect and lead to errors in inventory optimization. The proposed model provides a distribution-free and data-driven solution approach to the problem to overcome the shortcomings of the mathematical model. In a supply chain, demand forecasting and inventory optimization directly impact the production, distribution, routing, scheduling, and many more decisions. In this context, the proposed models and methodologies have numerous applications across supply chains of various industries, including fashion, food, energy, electronics, and media.

Keywords: Data-driven Decision Models; Artificial Intelligence; Demand Forecasting; Inventory Optimization; Big Data; Predictive Analytics; Prescriptive Analytics; Judgmental Forecasting; Time series methods; Deep Learning; Machine Learning; Evolutionary Optimization Algorithm; Temporal Aggregation; Cross-temporal Aggregation; Retail; Manufacturing.

सार

व्यवसाय जटिल और प्रतिस्पर्धी व्यावसायिक वातावरण के कुशल प्रबंधन के लिए डेटा की शक्ति का उपयोग करने और कृत्रिम बुद्धिमत्ता की तकनीकों का उपयोग करने के लिए अपनी रणनीति बना रहे हैं। विशाल डेटा की बढ़ती उपलब्धता और मशीन शिक्षण के क्षेत्र में हालिया प्रगति ने *संचालन और आपूर्ति श्रृंखला प्रबंधन क्षेत्र* में समस्याओं के लिए *डेटा-संचालित समाधान* विकसित करने पर फर्मों का ध्यान केंद्रित किया है। परंपरागत रूप से, संचालन और आपूर्ति श्रृंखला प्रबंधन क्षेत्र की समस्याओं को बड़े पैमाने पर गणितीय मॉडलिंग, अनुकूलन और अनुभवजन्य अध्ययनों के माध्यम से निपटाया जाता है। हाल के वर्षों में, व्यावसायिक समस्याओं को सुलझाने के लिए अनुसंधान का ध्यान डेटा और डेटा मॉडलिंग पर गया है। जिसे डेटा विश्लेषण विद्या के रूप में जाना जाता है। डेटा विश्लेषण विद्या और संचालन और आपूर्ति श्रृंखला प्रबंधन क्षेत्र के ज्ञान के एकीकरण से संचालन और आपूर्ति श्रृंखला के अनुकूलन के नियमों को प्राप्त किया जा सकता है।

डेटा विश्लेषण विद्या में, निर्णयकर्ता भविष्य के बारे में जानकारी प्राप्त करने के लिए ऐतिहासिक डेटा में पैटर्न को बाह्य गणन करने के लिए डेटा-आधारित मॉडल विकसित करते हैं, और फिर व्यावसायिक समस्याओं का प्रभावी समाधान प्राप्त करने के लिए इन अंतर्दृष्टि का अनुकूलन मॉडल में उपयोग करते हैं। भविष्य के परिणामों के बारे में अंतर्दृष्टि प्राप्त करना क्रियात्मक अंतर्दृष्टि के रूप में जाना जाता है, जबकि कार्रवाई योग्य अंतर्दृष्टि प्राप्त करने के लिए अनुकूलन मॉडल में भविष्य कहनेवाला विश्लेषण के परिणामों का उपयोग किया जाता है।

इस शोध कार्य में, आपूर्ति श्रृंखला पूर्वानुमान और संख्यापत्र इष्टतमीकरण में विभिन्न चुनौतियों का सामना करने के लिए भविष्य कहनेवाला और क्रियात्मक अंतर्दृष्टि मॉडल विकसित किए गए हैं। यह शोध कार्य मांग पूर्वानुमान मॉडल के आधार पर बड़े डेटा डेटा विश्लेषण और मशीन शिक्षण का प्रस्ताव करके एक जटिल व्यावसायिक वातावरण में मांग (बिक्री) पूर्वानुमान समस्या का समाधान करता है। प्रस्तावित मांग पूर्वानुमान मॉडल में एक नई पूर्वानुमान पद्धति विकसित की गई है जो एक सामूहिक प्रभाव कलनविधि के माध्यम से दीर्घकालिक-अल्पकालिक-स्मृति तंत्र और यादृच्छिक वन को इकट्ठा करती है। नई पूर्वानुमान पद्धति समय सामयिक और

कोवरिएट्स दोनों प्रकार के जटिल संबंधों को मॉडल कर सकता है, जो इसे अन्य अत्याधुनिक पूर्वानुमान विधियों की सटीकता में बढ़त प्रदान करता है। विश्लेषण के लिए ४२३५ मांग श्रृंखला जिसमें संरचित और असंरचित डेटा (जिसे "विशाल डेटा" कहा जाता है) का एक बड़ा नमूना उपयोग किया गया है। यह देखा गया कि प्रस्तावित पूर्वानुमान पद्धति परिचालन और सामरिक निर्णयों की मांग योजनाओं को विकसित करने के लिए सटीक पूर्वानुमान प्रदान में सक्षम है।

आगे के अनुसंधान कार्य में, अपेक्षाकृत लंबी अवधि के पूर्वानुमान प्रदान करने में सक्षम मांग पूर्वानुमान निर्णय मॉडल का विस्तार किया गया है। इन परिस्थितियों में विशाल डेटा मॉडल लागू नहीं होते हैं। प्रस्तावित निर्णय मॉडल गणितीय रूप से अर्थमितीय समय-श्रृंखला और मशीन शिक्षण मॉडल से विशेषज्ञों और मात्रात्मक पूर्वानुमान से निर्णय अनुमानों को एकीकृत करता है। इस काम के माध्यम से, यह पता लगाया गया है कि क्या मानव निर्णय का उपयोग अभी भी कृत्रिम बुद्धिमत्ता के युग, यानी मशीन शिक्षण में उपयुक्त है।

यह ज्ञात है कि आपूर्ति श्रृंखला को रणनीतिक, सामरिक और परिचालन निर्णय लेने के लिए लंबे समय तक समेकित पूर्वानुमानों की आवश्यकता होती है। इन पूर्वानुमानों का सटीक और सुसंगत होना आवश्यक है। हालांकि, आपूर्ति श्रृंखला में लंबे समय तक चलने वाले पूर्वानुमानों के लिए भविष्यवाणियों के विभिन्न तरीकों का उपयोग करने से योजना और निर्णयों के विभिन्न स्तरों पर पूर्वानुमानों में असंगति पैदा होती है। यह प्रबंधन में असंगति और संगठन के संसाधनों के अपव्यय की ओर ले जाता है। इस प्रकार, एक नये आपूर्ति श्रृंखला पूर्वानुमान चौखटा, जो अस्थायी और क्रॉस-अनुभागीय श्रेणीबद्ध पूर्वानुमान का एक संयोजन है, आपूर्ति श्रृंखला के सभी स्तरों पर सुसंगत पूर्वानुमान उत्पन्न करने के लिए प्रस्तावित किया गया है। प्रस्तावित चौखटा आपूर्ति श्रृंखलाओं के विभिन्न स्तरों पर सटीक और सुसंगत पूर्वानुमान प्रदान करता है।

अंतिम मॉडल में, भविष्य विश्लेषण विद्या को क्रियात्मक विश्लेषण विद्या मॉडल से जोड़ा गया है और डेटा-संचालित संख्यापत्र इष्टतमीकरण मॉडल विकसित किया गया है। मशीन शिक्षण और इष्टतमीकरण मॉडल का उपयोग करके एक क्षमता अवरोध के साथ बहु-उत्पाद संख्यापत्र प्रबंधन समस्या का समाधान किया गया है।

समाचार संख्यापत्र प्रबंधन समस्या के गणितीय समाधान संख्यापत्र प्रबंधन साहित्य में उपलब्ध हैं। हालांकि, ये उपलब्ध समाधान मांग वितरण और अन्य मापदंडों के बारे में कई धारणाएं बनाते हैं, जो अक्सर गलत होती हैं और संख्यापत्र इष्टतमीकरण में त्रुटियों का कारण बनते हैं। प्रस्तावित मॉडल गणितीय मॉडल की कमियों को दूर करने के लिए एक धारणा-मुक्त और डेटा-संचालित समाधान प्रदान करता है। आपूर्ति श्रृंखला में, मांग पूर्वानुमान और संख्यापत्र इष्टतमीकरण का उत्पादन, वितरण, रूटिंग, शेड्यूलिंग और कई और फैसलों पर सीधा प्रभाव पड़ता है। इस संदर्भ में, प्रस्तावित मॉडल और कार्यप्रणाली के विभिन्न उद्योग जैसे कि खाद्य, ऊर्जा, स्वास्थ्य देखभाल और अन्य की आपूर्ति श्रृंखलाओं में कई अनुप्रयोग हैं।

संकेतशब्द : डेटा-संचालित निर्णय मॉडल, कृत्रिम बुद्धिमत्ता; मांग पूर्वानुमान; संख्यापत्र इष्टतमीकरण; भविष्यिक विश्लेषण विद्या; क्रियात्मक विश्लेषण विद्या; पूर्वानुमान; न्यायिक पूर्वानुमान; समय श्रृंखला; मशीन शिक्षण; समय सामयिक एग्रीगेशन; क्रॉस- समय सामयिक एग्रीगेशन; खुदरा; विनिर्माण।

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LIST OF VARIABLES AND PARAMETERS

Chapter 3

- X_t : the input vector at time step t
- h_t : the output vector at time step t
- s_t : the vector for cell state t
- $\tilde{s}_t$: the vector for a candidate value for input gate
- $b_f, b_i, b_{\tilde{s}}, b_o$: bias vectors
- $\sigma(\cdot)$: denotes the sigmoid function $\left(f(x) = \frac{1}{1+e^{-x}}\right)$
- $W_{f,x}, W_{f,h}, W_{i,x}, W_{i,h}, W_{o,x}, W_{o,h}, W_{\tilde{s},x}, W_{\tilde{s},h}$: weight matrices for input and outputs for the three gates (forget gate, input gate, and output gate), and cell state
- f_t, i_t, o_t : vectors of values obtained after activation of the three gates

Chapter 4

- $S_{t,i}$: represent the number of searches with selected keywords ($k_{t,i}$)
- $R_{t,i}$: total number of search queries in geographical area i in total N_w weeks
- $GI_{t,i}$: Google search index
- Y_t : time-series vector
- $\hat{y}_t$: predictions from the LSTM networks
- y_{rf} : predictions from the RF

Chapter 5

- $\{L_{t+1}^E, M_{t+1}^E, U_{t+1}^E\}$: lower, most likely, and upper bound, respectively, of the interval for the expert's forecast
- I_F : Internal expert's judgmental demand forecasts
- E_F : External expert's judgmental demand forecasts
- X^c : interval mid-point series
- X^r : half range interval series
- w_1 and w_2 : weights given to forecasts of expert 1 and expert 2

- C_{F_1} : combined experts forecast
- C_{F_2} : combined statistical forecast

Chapter 6

- CX : Total Quantity sold on all channels
- P_i : Product i , $i \in 1, 2, \dots, n$
- CP : Total Quantity sold of a specific product on all channels
- C_{ON} : Online Channel
- C_{OFF} : Offline Channel
- S_{ON} : Online Store
- $S_{OFF(j)}$: Offline Store j , $j \in 1, 2, \dots, M$
- SP : Total quantity sold of a specific product at a specific store.
- $\hat{y}_h$: base forecast for each level with horizon h can be represented by
- S : summing matrix
- SG : reconciliation matrix

Chapter 7

- d_i : random variable for the demand for an item i
- c_i : purchasing cost for each unit of item i
- p_i : selling price for each unit of item i
- h^i : overage cost for each unit of item i
- b^i : underage cost for each unit of item i
- m : total no. of items/products
- G_n : total no. of items in a product group
- C : total resource capacity for all products of a product group
- Q_i or Q^i : order quantity for item i
- $\pi_i(Q_i)$: total cost of inventory for item i
- Q_i^u : unconstrained order quantity for item i
- α^i : the critical fractile (optimal service level) for unconstrained newsvendor item i
- β^i : is the ratio of the capacity required to the marginal revenue for an item i

LIST OF ABBREVIATIONS

ACF: Auto-correlation function

ADAM: Adaptive moment estimation

AI: Artificial Intelligence

AIC: Akaike Information Criterion

ANN/ FNN: Artificial/Feedforward Neural Network

AR: Autoregression

ARIMA: Autoregressive integrated moving average

ARIMAX: Autoregressive integrated moving average with external regressors

ARMAE: Average relative mean absolute error

ARMAPE: Average relative mean absolute percentage error

ARME: Average relative mean error

ARMSE: Average relative mean squared error

BAM: Bias adjustment mechanism

BIC: Bayesian Information Criterion

CART: Classification and regression trees

CH: Cross-sectional Hierarchies

CS-HF: Cross-sectional hierarchical forecasting

CT-HF: Cross-temporal hierarchical forecasting

DFDM: Demand forecasting decision model

DFM: Demand forecasting model

DL: Deep Learning

DM: Diebold and Mariano Test

DNN: Deep neural networks

ETS: Error, Trend, Seasonality

FMCG: Fast moving consumer goods

FVA: Forecast Value-added Analysis

GA: Genetic Algorithm

GLS: Generalised least square

HF: Hierarchical Forecasting

LSTM: Long-short-term-memory

MA: Moving Average

MAE: Mean absolute error

MAPE: Mean absolute percentage error

ME: Mean error

ML: Machine Learning

MLR: Multiple linear regression

NVM: Newsvendor Model

NVP: Newsvendor Problem

PACF: Partial auto-correlation function

PCA: Principal components analysis

POS: Point-of-sales

PT: Pesaran and Timmermann Test

QR: Quantile regression

QR-ML: Quantile regression-machine learning

ReLU: Rectified linear unit

RF: Random Forest

RMSE: Root mean squared error

RMSPROP: Root mean square propagation

RNN: Recurrent Neural Network

SGD: Stochastic gradient descent

SKU: Stock keeping unit

SVM: Support Vector Machine

TA: temporal aggregation

TD: temporal disaggregation

TD-NVM: Top-down newsvendor model

TH: Temporal Hierarchies

TPR: Temporary price reduction

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