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Review and analysis of artificial intelligence methods for demand forecasting in supply chain management

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Abstract

The proper selection of a demand forecasting method is directly linked to the success of supply chain management (SCM). However, today's manufacturing companies are confronted with uncertain and dynamic markets. Consequently, classical statistical methods are not always appropriate for accurate and reliable forecasting. Algorithms of Artificial intelligence (AI) are currently used to improve statistical methods. Existing literature only gives a very general overview of the AI methods used in combination with demand forecasting. This paper provides an analysis of the AI methods published in the last five years (2017-2021). Furthermore, a classification is presented by clustering the AI methods in order to define the trend of the methods applied. Finally, a classification of the different AI methods according to the dimensionality of data, volume of data, and time horizon of the forecast is presented. The goal is to support the selection of the appropriate AI method to optimize demand forecasting.

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Keywords: Demand Forecasting; Supply Chain Management; Artificial Intelligence; Machine Learning; Deep Learning; Review; Analysis

1. Introduction

The era of stable markets is history. Nowadays companies are confronted with highly complex scenarios characterized by unpredictable situations such as monetary crisis, pandemics, climate change, supply constraints. Additionally, growing demand for fully customized products in the shortest possible time has aggravated this situation [1]. This increasing complexity hinders the desired transparency of material and information flow between supply chain members, which is essential to ensure the success of supply chain planning (SCP) and to improve the overall value chain resilience [2]. Demand forecasting represents a solid basis for planning and procurement processes that make the supply chain more responsive and efficient [3,4]. Therefore, the improvement of demand forecasting methods has become more and more important for manufacturers, distributors and retailers [5–7]. Different methods are adapted to forecast demand. These can be statistical, AI-based, or hybrid methods, which combine the characteristics of a statistical model with a model from the AI domain [8]. Statistical methods provide accurate forecasting results and are very useful. Currently, due to increasing data dimensions and data volume, these classical methods face challenges and do not always meet the requirements of manufacturing companies [6,9,10]. With the use of AI in SCM new methods have been proposed, which combine traditional time series forecasting with machine learning methods or use artificial neural networks to refine and improve the demand forecasting process [11]. Machine learning (ML) is a subarea of AI which works with self-learning algorithms. ML methods aim to improve their results based on experience gained from available historical data [12]. Furthermore, ML methods have been shown to perform well with large amounts of noisy data, such as those typically found in historical demand data. Due to

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the large number of existing AI methods and the lack of transparency in their classification, Liu et al. propose a taxonomy to classify them into traditional ML methods and deep learning methods. Subsequently, each category can be divided into supervised and unsupervised learning [13]. Demand forecasting represents a research field in continuous development [14], which increases the complexity of identifying a suitable method for each scenario. In addition, the current literature provides a limited overview of demand forecasting methods, especially in relation to manufacturing companies. Therefore, the aim of this paper is the review and analyze currently used AI methods, focusing on demand forecasting in SCM of manufacturing networks. Furthermore, a classification is presented by clustering the AI methods in order to define the trend of the methods used. Finally, this publication presents a classification of different methods based on data characteristics, which supports the AI method selection for demand forecasting based on user requirements.

2. Methodology

This paper uses a structured literature review to identify existing AI methods for demand forecasting. A structured literature review is relevant for the analysis of a specific topic [15] and the identification of knowledge gaps [16]. Several methods for conducting a literature review are currently available. This publication adopts the concept presented by Snyder et al. [16] and follows the approach proposed by Patel et al. [17]. The objective of this review is to analyze the state-of-the-art methods from different AI areas applied to demand forecasting, specifically in the area of SCM, with a focus on manufacturing. The databases used to collect the publications are Web of Science, IEEE Explore and Springer Publishing. All three databases are searched and accessed in October 2021. Subsequently, the following search sequence is defined in combination of Strings with Boolean operators: ("demand forecasting" OR "demand prediction") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("supply chain management"). The search range is restricted to publications from the last five years (2017 - 2021). In the first stage, 92 publications that met the initial requirements are evaluated. In the following sections, the authors consider only publications related to the manufacturing domain.

3. Structured literature review

The structural literature search identified 23 publications that fulfilled the requirements defined in the methodology. First the terminology is defined and subsequently the characteristics found are analyzed.

3.1 Definition of terminology

This section defines the terminology used to analyze the publications. The analyzed fields are defined as *Area*, *SCM*, *Data,* and *AI* (Table 1). The purpose of the table is to allow a comparison between supply chain (SC) members and how much data is collected for demand forecasting and shows which related AI methods are applied.

The first field in the table *Area* shows the industry sector of the publications. The second field *SCM* defines the members(s) of the supply chain involved in the forecasting process.

The field *Data* describes the dataset that is used for training and validation of the AI algorithms. This field has three subfields to describe the datasets in more detail to determine the volume of the dataset. Each dataset can consist of several input attributes. For that reason, the dataset is analyzed according to dimensions, divided into univariate and multivariate, under the field *Dimensions*. The *Range* of data collection is provided consistently in months for better comparison between publications. In addition, the *Frequency* of data collection can be daily, weekly, monthly, or quarterly.

Furthermore, all publications are analyzed according to the AI methods used to predict demand. In the AI field, the publications are analyzed according to four subfields. All AI methods used in the publications are listed in the subfield *Method*. The publications use a single method (A), several methods (A, B), and combined (A+B) methods. The *Time horizon* field describes the horizon forecasted by the AI method. The time horizon is defined as short-term (hourly, daily, weekly), medium-term (monthly), and long-term (yearly). The metrics applied in the publications to evaluate the AI methods are listed under the subfield *Metrics*. *Tool* represents the last subfield and lists the software or programming language used for the implementation.

3.2 Overview and analysis of the literature

According to the industrial sector, seven publications come from the logistics area. After analyzing the supply chain members involved in the forecasting process, four publications analyze the situation from the retailer's point of view and seven from the manufacturer's perspective.

Concerning the analyzed field of data, 55 percent of the data are univariate input data and only historical data sales are used without additional attributes. Concerning multivariate inputs, the publications consider a minimum of 3 attributes [5] and a maximum of 16 additional attributes [6,18] in demand forecasting. Typical additional attributes used throughout the literature are climate, temperature, locality, etc. Furthermore, the data ranged from 1 to 168 months and almost 50 percent of the data were collected daily. The other half of the data is collected on a weekly or monthly basis. All AI methods used in the publications are specified in the table to provide a general overview. They will be analyzed in detail in section 4. The analysis shows a tendency towards short- to medium-term forecasts. Only a single publication forecasted long-term demands. The metrics most used in the publications are relative mean square error RMSE (x10), mean absolute percent error MAPE (x6), mean absolute error MAE (x5) and mean square error MSE (x5). Finally, the most used software is Python (x6), followed by R (x5) and MATLAB (x4).

Table 1. Overview of literature using AI-based forecasting methods in SCM in the manufacturing domain from 2017 to 2021.

Area	SCM	Data			AI				
		Dimension	Range months	Frequency	Method[a]	Time horizon	Metrics[b]	Tool	
Automotive	Manufacturer	Multivariate	108	Weekly	MLP, RF, SVR	Short-term	NMAE	R	[19]
Automotive	Manufacturer	Univariate + Multivariate	72	Quarterly	AdaBoost, ANN, GB	Medium-term	RMSE, R^2	-	[5]
Manufacturing	Retailer	Univariate	168	Monthly	ANN, ARIMA + LR	Medium- term	AE, MAPE, TE	R	[20]
Logistics	Retailer	Multivariate	2	Daily	Classification DT	Short-term	ACC, PR, RE	WEKA	[4]
Building and Construction	Manufacturer	Multivariate	72	Monthly	ARIMAX + ANN	Medium-term	FA, MAPE	-	[21]
Logistics	Manufacturer	Multivariate	4.5	Weekly	K-means + QRF + RF	Medium-term	PICP, PINAW, RMSE	R	[22]
Logistics	Retailer	Univariate	34	Daily	ANN	Medium-term	MSE, R^2	MATLAB	[23]
Manufacturing	Manufacturer	Univariate + Multivariate	48	Monthly	MLP	Medium-term	ACC	MATLAB	[18]
Logistics	Retailer	Multivariate	1	Daily	DT, KNN, Naive Bayes	Short-medium-term	MAPE	-	[24]
Tele-communication	Manufacturer	Univariate	36	Quartal	GB	Medium-term	MAD, MAPE, MSE, RMSE	-	[25]
Warehouse	Distributor	Univariate	43	Daily	LSTM	Short-term	MSE	Python	[9]
Logistics	Retailer	Multivariate	30	Daily and weekly	ANN, LSTM + RF, LSTM, RF	Short-medium-term	MAE, MSE, RMAE, RME, RMSE	Python, R	[6]
Manufacturing	Retailer	Univariate	36	Monthly	LSTM, BLSTM	Medium-term	MAE, MASE, RMSE, sMAPE	MATLAB	[10]
Service Provider	Retailer	Univariate	48	Daily	ARIMA + Theta + Feed Forward MLP, K-means	Short- medium-term	MAE, MAPE, MASE	Azure	[8]
Store	Retailer	Multivariate	36	Weekly	ANN	Long-term	MSE	MATLAB, R	[26]
Logistics	Retailer	Multivariate	-	-	ANN, NRS + SVM	Short-term	MAPE	MATLAB	[27]
Store	Retailer	Univariate	30	Daily	DNN, GB	Short-term	MAE, RMSE	Python	[28]
Store	Retailer	Univariate	48	Monthly	LSTM	Medium-term	RMSE	Python	[29]
-	Retailer	Univariate	72	Monthly	LSTM, MLP, RF, XGBoost	Medium-term	RMSE	Python	[30]
Electronics	Distributor	Univariate	26	Weekly	ARIMA+RNN	Medium-term	MAE, MASE, RMSE	R	[31]
Logistics	Retailer	Univariate	2	Daily	ANN, DT, KNN, Part classifier, RF, SVM	Short-term	ACC, PR, RE	WEKA	[32]
Logistics	Retailer	Multivariate	3	Daily	DT, GB, LR, RF	Short-term	r, RMSE	Python	[33]
Defence	Manufacturer	Multivariate	-	-	DT, MLP, RF, SVM, XGBoost	-	ACC, PR, RE	Python	[34]

[a] AdaBoost: Adaptive Boosting, ANN: Artificial Neural Network, ARIMA: Autoregressive Integrated Moving Average, ARIMAX: ARIMA model with an exogenous variable, BLSTM: Long Short-Term Memory (Forward/Backward), DNN: Deep Neural Network, DT: Decision Tree, GB: Gradient Boosting, LR: Logistic Regression, LSTM: Long Short-Term Memory (Forward), MLP: Multi-Layer Perceptron, NRS: Neighborhood Rough Set, QRF: Quantile Regression Forest, RF: Random Forest, RNN: Recurrent Neural Network, SVM: Support Vector Machine, SVR: Support Vector Regression, XGBoost: Extreme Gradient Boosting

[b] ACC: Accuracy, AE: Absolute Error, FA: Forecast Accuracy, MAD: Mean Absolute Deviation, MAPE: Mean Absolute Percent Error, MASE: Mean Absolute Scaled Error, MAE: Mean Absolute Error, MSE: Mean Square Error, NMAE: Normalized Mean Absolute Error, PICP: Prediction Interval coverage probability, PINAW: Prediction interval normalized average width, r: Correlation coefficient , PR: Precision, RE: Recall, RMAE: Relative mean absolute error, RME: Relative mean error, RMSE: Relative mean square errors, R^2: Coefficient of determination, sMAPE: symmetric mean absolute percentage error, TE: Total Error

Table 2. Classification of the best performing AI methods rated by the authors in their AI areas.

Machine learning methods							
Traditional machine learning methods				Deep learning methods		Ensemble methods	
Unsupervised Learning		Supervised Learning		Unsupervised Learning	Supervised Learning	Boosting	Bagging
Clustering	Dimension Reduction	Classification	Regression				
K-means [8,22]	NRS [27]	DT [4] Naive Bayes [24] SVM [27] Part classifier [32]	LR [20] QRF [22] RF [33]	-	ANN [21,23,26] LSTM [6,9,29] BLSTM [10]; RNN [31] MLP [8,18,19,30]	AdaBoost [5] GB [25,28] XGBoost [34]	RF [6,22]

4. Analysis of AI methods used for demand forecasting in SCM

This section classifies the AI methods used by means of a taxonomy according to their learning approaches for further analysis. Then, a classification of AI methods based on their data characteristics is proposed.

4.1 Classification of the best performing AI methods

In the previous section, Table 1 indicates all the AI methods used and compared in each publication. For a more precise and detailed analysis, Table 2 shows only the method, or combination of them, that provides the best results in each publication. Therefore, Table 2 offers a classification of the 23 "winners" AI methods according to a taxonomy of AI disciplines. Due to the diversity of AI methods, these are classified to provide a more clear overview. The authors aim to provide transparency regarding the classification of the AI methods used based on their learning approaches. In order to evaluate the trend between traditional ML methods and deep learning methods, the authors employ the taxonomy proposed by Liu et al. [13]. Additionally, ensemble methods are also considered.

In the field of supervised and deep learning, 12 publications are observed. The most widely used methods in this field are Multi-Layer Perceptron MLP, Long Short-Term Memory LSTM, and Artificial Neural Network ANN. Concerning traditional ML methods, higher use of supervised learning methods is noticed. Seven methods use classification and regression algorithms. Regarding unsupervised learning, three publications previously applied dimension reduction and clustering of their data. These methods are not used to directly forecast demand. They are applied to the data to improve demand forecasting. Dimension reduction is used to eliminate unnecessary dimensions and thus improved the accuracy of the forecast [27]. Clustering is used to group products with similar properties to forecast the demand of an entire cluster [8,22]. In addition, ensemble methods are used in six publications. The general purpose of an ensemble method in ML is to combine the predictions of several regression or classification methods to achieve a better prediction.

4.2 Classification of AI methods by data characteristics

To support manufacturing companies in selecting suitable AI methods, this section offers a classification of AI methods according to their characteristics. Punia et al. [6] propose the idea of classifying demand forecasting methods according to the dimensionality of data and volume of data used to train and test the algorithms. This idea represents an initial approach in identifying and suggesting a suitable method, but only offers a general guideline for method selection. Based on this understanding, Table 3 provides a more detailed and complete classification of the 23 AI methods used in current literature. The parameters to be considered are the dimensionality of the data, the volume of data, and the time horizon over which the methods offer the best results. According to the dimensionality, three classes are defined. Univariate dimensionality corresponds only to historical demand data. Multivariate dimensionality is divided into AI methods using ten attributes or less and those using more than ten attributes. The volume of the data represents the range of the data as a function of the frequency of the data.
Some publications report the volume of data for a set of products. In order to make a fair classification, only the volume of data for a single product is analyzed. Four categories are defined according to the volume of data. The low category includes methods that process up to 500 input data. This is followed by the medium category with more than 501 up to 1000 input data. In addition, the high volume represents methods with more than 1001 data. Table 3 shows a field with the designation "non-defined". This is because not all publications provide a detailed statement of the data used. Finally, the proposed classification considers the time horizon over which the methods perform well. This is indicated in brackets next to each AI method in Table 3. For more information about the definition of the time horizon see section 3.1.

4.3 Analysis of AI methods

The success of SCM depends on the effective exchange of information between members in the SC. When it comes to demand forecasting, upstream members are highly dependent in terms of information provided by the downstream members.

Table 3. Classification of the best performing AI methods rated by the authors by data characteristics.

Volume \ Dimension	Univariate	Multivariate (Attributes: 2-10)	Multivariate (Attributes: 11-n)
Non-defined	-	[34] XGBoost (-)	[27] NRS+SVM (Short-term)
Low (1-500)	[32] Part classifier (Short-term) [25] GB (Medium-term) [30] MLP (Medium-term) [29] LSTM (Medium-term) [10] BLSTM (Medium-term) [20] ARIMA*+LR (Medium-term) [31] ARIMA*+RNN (Medium-term)	[33] RF (Short-term) [4] DT (Short-term) [24] Naïve Bayes (Short-medium-term) [19] MLP (Medium-term) [21] ARIMAX*+ANN (Medium-term) [22] K-means+QRF +RF (Medium-term)	[6] LSTM+RF (Short-term) [18] MLP (Medium-term) [26] ANN (Long-term)
Medium (501-1000)	[28] GB (Short-term)	[5] AdaBoost (Medium-term)	[6] LSTM+RF (Medium-term)
High (From 1001)	[9] LSTM (Short-term) [8] ARIMA*+MLP +Theta* (Short-medium-term) [23] ANN (Medium-term)	-	-

AI Methods: AdaBoost: Adaptive Boosting, ANN: Artificial Neural Network, ARIMA: Autoregressive Integrated Moving Average, ARIMAX: ARIMA model with an exogenous variable, BLSTM: Long Short-Term Memory (Forward/Backward), DT: Decision Tree, GB: Gradient Boosting, LR: Logistic Regression, LSTM: Long Short-Term Memory (Forward), MLP: Multi-Layer Perceptron, NRS: Neighborhood Rough Set, QRF: Quantile Regression Forest, RF: Random Forest, RNN: Recurrent Neural Network, SVM: Support Vector Machine, XGBoost: Extreme Gradient Boosting.

* Statistical method used for hybrid

Hence, it is important to choose an appropriate AI method to avoid demand distortion. The demand forecasting process is additionally influenced by several attributes such as location, traffic. Thus, the dimension of data is important not only for the representation of real scenarios but also for the selection of a suitable AI method. This research shows the clear and successful trend of applying AI methods with multivariate datasets to improve forecasting accuracy [6,22–25,29,33,34]. Almost 50 percent of the analyzed publications use a multivariate data input. In comparison, the study by Gonçalves et al. [19] analyzed 15 publications between 2004 and 2016. 90 percent of these publications worked with univariate data. Especially deep learning methods perform well with unstructured and high-volume data [35]. Table 3 confirms that most AI methods that use multivariate data are based on deep learning techniques.

The volume of data plays an important role in the selection of an AI method. This paper points out that currently, most AI methods work with a low volume of data. This is due to the difficulty in accessing real data and technical limitations in terms of software and hardware. Additionally, the few methods that use a high volume of data belong to the deep learning area.

Furthermore, the use of hybrid methods (marked with an asterisk in Table 3) significantly increases the demand forecasting process. Although statistical methods are generally used with linear data, they perform well in combination with AI methods. This means that hybrid methods allow modeling demand data with linear and non-linear behavior. Such data behavior is characteristic of customer demand in complex supply chains.

Table 3 indicates the total absence of methods in the field of big data, i.e., data characterized by multivariate dimension and high volume of data. This is because the handling of Big Data requires unique architectures that exceed the typical technological requirements in terms of capacity, storage, processing and data analysis techniques [35].

Finally, this analysis points out that most of the examined AI methods forecast the demand in the short- and medium-term with a good performance.

5. Conclusion

Accurate demand forecasting enables manufacturing companies to increase overall supply chain resilience. AI methods alone or in combination with statistical methods significantly improve the accuracy of demand forecasting methods. Additionally, in order to avoid demand distortion - bullwhip effect - and thus ensure the success of the supply chain, transparent communication between the members involved in the demand forecasting process is essential. However, this publication shows that most of the literature reviewed concentrates only on demand forecasting from the retailer's perspective. This shows the absence of "collaborative forecasting" which is indispensable for upstream members of the supply chain.

This publication analyses 23 different methods successfully applied in demand forecasting between the years 2017 and 2021. This analysis shows the clear trend of using deep learning techniques. The methods most used are Multi-Layer Perceptron MLP, Long Short-Term Memory LSTM, and Artificial Neural Network ANN, all of them corresponding to the deep learning area.

With respect to the data, techniques such as clustering and dimension reduction are used to improve data quality and thus demand forecasting. Furthermore, the consideration of additional attributes such as weather, location, and events, in most cases, improves the accuracy of demand forecasting. This publication also shows a clear gap in the existence of AI methods that perform in the field of big data, i.e., data with several variables and a high volume of data. Hybrid methods represent hereby a good candidate to deal with these issues. Finally, this publication classifies the AI methods analyzed throughout this literature review by their characteristics such as dimensionality of data, volume of data, and time horizon of the forecast. This classification supports manufacturing companies in the process of selecting an appropriate AI method for forecasting customer demand.

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