Machine Learning applications in supply chains

An emphasis on neural network applications

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***Abstract*—Machine Learning or the ability of a machine to learn automatically has garnered a lot of interest in the last years. It has proven to be a valuable tool for aiding decision makers and improving the productivity of enterprise processes, thanks to its ability to learn and find interesting patters in data. Thereby, supply chains can take advantage from Machine Learning to improve their productivity thanks to the better forecasts. As such, this paper examines multiple algorithms of Machine Learning and explores their applications for the various supply chain processes.**

Keywords—Machine Learning; Supply Chain; Neural Networks; Demand forecasting

I. INTRODUCTION

In the literature of supply chains, multiple authors present various definitions. For instance, reference [1] define the supply chain as “a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer”, addressing the necessity of at least three entities, and the multiple types of flows between them. On the other hand, reference [2] state that “a supply chain is the set of entities that are involved in the design of new products and services, procuring raw materials, transforming them into semi-finished and finished products, and delivering them to the end customers”. As such, we define the supply chain as a set of three or more entities - suppliers, manufacturers, distributors, warehouses, third-party service providers, retailers, customers, etc.- through which exists upstream and downstream flows of materials, information, and finances, with the ultimate goal of meeting the customer's demand. Each entity within the chain involves activities such as procuring raw materials, their transformation into semi-finished or finished products, the distribution, the customer service and other logistic operations.

A supply chain’s success depends on the accuracy of forecasts especially those of the demand. However, supply chains suffer from the effects of uncertainty which results in the bullwhip effect, a phenomenon that describes the upstream amplification in the demand variability. So, the increase in the accuracy of the forecasts entails the reducing of this effect as well as the total costs of the supply chain. Thus, Machine Learning techniques constitute a real asset for supply chains, since they give better forecasts than the more traditional approaches. Although there some reviews of predictive analytics in supply chains, papers either address predictive and Big data analytics for supply chains in general and only mention machine learning algorithms in passing [3][4][5], or they only address machine learning algorithms for demand forecasting like reference [6]. The present paper however aims to review the literature of the applications of the major machine learning algorithms for the upstream and downstream processes of the supply chain.

The paper is structured as follows: in Section 2, the research methodology is presented. In section 3 a panoply of machine learning algorithms is presented, including neural networks. In Section 4, the applications of these algorithms in supply chains are reviewed. In section 5, applications of different types of neural networks are presented. Finally, in Section 6, some conclusions are discussed.

II. RESEARCH METHODOLOGY

The research process started with the identification of the keywords to use when researching the literature, before combining them into the following search string:

(machine learning OR linear regression OR logistic regression OR neural network OR support vector machine OR data mining OR deep learning) AND (supply chain OR logistics).

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This search string is then used on the Science Direct Database, on the title the abstract and the keywords of articles published after 2010. The selection resulted in 42 articles.

III. TAXONOMY OF MACHINE LEARNING LITERATURE

A. Machine Learning

Machine Learning is a type of artificial intelligence that gives machines the ability to learn automatically from past data without human intervention, by extracting patterns from raw data. There are two main types of learning, supervised learning and unsupervised learning [7]. In supervised learning data is structured and labeled into inputs and outputs, a machine is given a set of inputs and their correspondent outputs with the objective of finding the relationship between the two. In unsupervised learning data is unlabeled, it aims to find patterns and structure in the data. These two types of learning are used mainly for four types of tasks [8]:

- Regression: a supervised leaning task for predicting continuous data.
- Classification: a supervised learning task for predicting discrete data, mainly predicting to which class a new example belongs given a set of previous examples [9].
- Clustering: an unsupervised learning task that aims to divide data into groups or clusters without having any previous information on them [10].
- Association: aims to discover interesting relations and generate rules between variables in large amounts of data.

B. Machine Learning algorithms

Various algorithms are used for Machine Learning. Among others are Neural Networks, Support Vector Machines, Regression, Decision Trees, Random Forests, Association Rule Learning, various classifiers, k-means algorithms, etc.

1) Support Vector Machines (SVM)

A supervised learning method that can be used for classification and regression problems, however, they are mostly suitable for handling high-dimensional, non-linear classification problems [11]. Given a training data set, each set of data belonging to one of two categories, an SVM algorithm predicts to which category a new example belongs [12].

2) Linear Regression (LR)

A well-known method massively employed to represent the relationship between the dependent variables and independent variables. It has been used for prediction in many fields, such as economics and management [13].

3) *Decision Trees (DT) and Random Forests (RF)*

Decision trees are graphs of decisions and their possible consequences. Each node in a decision tree contains a question relative to a particular attribute. Leaf nodes are groups of instances that receive the same class label [14]. Decision trees are also called regression trees (RT) when the variable is of continuous nature. Decision trees have low bias but they tend to overfit the training set. That is where random forests come in handy, they are constituted of multiple decision trees trained on different parts of the data set and random subsets of the features, they predict by averaging the predictions of all the individual decision trees [15].

4) K-means algorithms

Introduced by [16], they are a set of unsupervised learning algorithms used for clustering. The k-means algorithm divides the data into k clusters that minimizes the “within groups sum of squared errors” [17].

5) HyperBox Classifier

Hyperboxes are used for enclosing data points and representing classes [8].

6) Gamma Classifier

The Gamma classifier is based on the Alpha-Beta associative memories [18]. It is a supervised technique which name is derived from the similarity operator that it uses: the generalized Gamma operator. This operator takes as input two binary vectors and a positive integer, then returns 1 if both vectors are similar -the integer is the degree of dissimilarity allowed- or 0 otherwise [19].

7) Neural Networks (NN)

Modeling with neural networks started in the early 1980 with the first business application in 1988 [20]. They were developed to create artificial systems that imitate the way the human brain learns and performs intelligent tasks [21]. They are a very powerful technique of learning that can be used for classification or approximation of an output given a set of inputs and they are capable of identifying the most complex linear or nonlinear input/output relationships.

They consist of a circuit of interconnected neurons inspired by the biological neurons of the human brain that activate when they encounter enough stimuli. The neurons are connected and organized as multiple interconnected layers [22]: the input layer, one or more hidden layers, and the output layer. The input layer is composed of nodes called dendrites that correspond to the input variables, whereas the output layer is composed of nodes called axons that correspond to the output variables [22]. The computation happens in the hidden layers. First, the hidden nodes receive input data from the first layer, they combine them with a set of coefficients or weights that either amplify or minimize the input, the resulting products are then added, finally, an activation function is applied to the sum to determine whether and to what amount the signal progresses through the network to affect the final result.

IV. THE SYNTHESIS OF APPLICATIONS OF MACHINE LEARNING IN SUPPLY CHAINS

A supply chain’s ultimate goal is to satisfy the customer’s demand all the while minimizing the cost as much as possible. However, a supply chain faces multiple obstacles, among which are supply risk and demand uncertainty which is the main cause for the bullwhip effect. So, to improve decision making in these cases, many researchers exploit Machine Learning algorithms to improve the predictions.

Fig.1 represents the number of articles that apply each of the machine learning algorithms previously presented. We

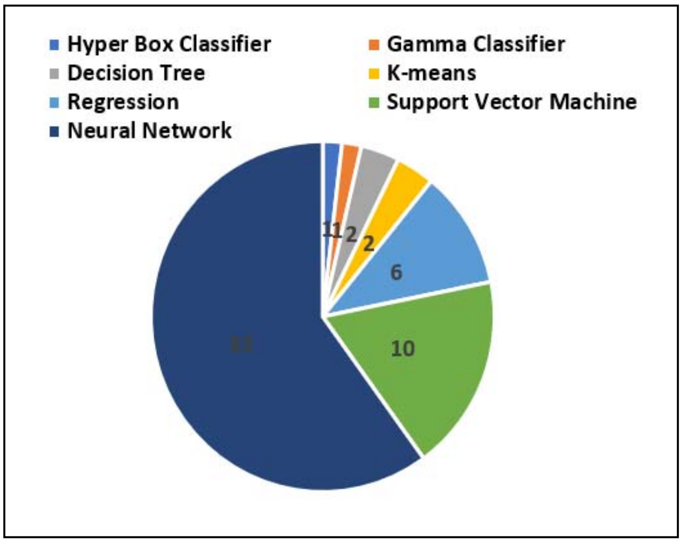

Fig. 1. Number of articles applying each machine learning algorithm

notice that the most used techniques are the neural networks followed by the support vector machine, and linear regression.

Machine learning algorithms are used in many phases of the supply chain, both downstream and upstream, mainly in the following processes: the planning, the procurement and supply management, the production, the inventory and storage, and finally the transportation and distribution.

Fig. 2 represents which machine learning algorithms are used in each of these different areas.

1) Planning

The driving force behind planning in any stage of the supply chain is demand forecasting. Reference [23] try to find the best demand forecasting model in a supply chain. They find that support vector regression (a variation of SVM) has better prediction performance compared to the RBF neural network. Reference [24] apply feed-forward NN and rule-based reasoning for demand management to recognize and classify demand patterns in order to determine the correct replenishment strategy. Reference [25] present a hybrid intelligent system combining the SVM and particle swarm optimization to forecast a seasonal nonlinear random and fuzzy demand series. This model is then proven to give better results than the ARMA model. Reference [26] propose a methodology for supply chain integration and uncertain demand forecasting by combining between ANFIS and a simple neural network. Reference [27] design a grey neural network to predict the demand after transportation disruption, this model ensures better accuracy than the traditional grey model GM(1,1). Reference [28] compare the Conditional Restricted Boltzmann Machine (CRBM), the Factored Conditional Restricted Boltzmann Machine (FCRBM), a feed-forward NN, a recurrent NN, and SVM for the prediction of energy consumption, the FCRBM outperformed all the other models. And, reference [22] present a short-term electric load forecasting model based on a Bayesian neural network learned by the Hybrid Monte Carlo algorithm, and state that it can overcome the overfitting problem that most neural networks suffer from.

Other forecasts aiding decision making in the planning phase include sales, costs and price forecasts. For instance, reference [29] use a neural network to predict sales of oral-care products. Reference [30] propose an intelligent system based on SVM for time-series classification, the resulting categories then share the same forecasting model. References [31] and [32] tackle the problem of seasonal sales forecasting in the fashion industry, the first using ANFIS neural network and the second using a neural network based model for medium-term fashion sales forecasting, which is then proven to perform better than ARIMA. References [33] and [8] attempt to predict the Cost-To-Serve - all costs of the activities needed to fulfill customer demand for a product through the supply chain- a customer. The former by applying regression and NN alternatively, and the latter by grouping the customers via a hyper-box based classifier. Reference [34] address the problem of predicting customer order prices by comparing a neural network and genetic programming, the former outperformed the latter. And Reference [35] use neural networks and quantile regression to predict truckers spot price in the freight transport process. Reference [36], on the other hand, apply k-medoids-a variant of K-means-to cluster manufacturing and logistic processes.

Thus, in a nutshell, the usefulness of machine learning algorithms in this context resides in improving the accuracy of various forecasts and investigating issues such as uncertainty, randomness, seasonality and the bullwhip effect.

2) Procurement and supply management

The main function explored by machine learning in this area is the supplier evaluation and selection, it is the process by which organizations evaluate and select which supplier to have a contract with.

References [37] and [21] use neural networks for supplier selection and performance evaluation. Reference [38] address sustainability via self-organized maps, while reference [39] combine between neural networks and multi-attribute decision analysis for supplier selection in a green supply chain.

Others resort to fuzzy neural networks to solve this problem. For instance, reference [40] study fuzziness by comparing ANFIS and a neural network. Reference [41] propose a hybrid ANFIS-neural network model to evaluate suppliers in two stages: first an ANFIS model is used to determine the most influential criteria on the supplier's performance, then, a multi-layer perceptron neural network is used to predict and rank the supplier's performance based on the criteria previously determined. And, reference [42] propose a novel fuzzy neural network for the evaluation of suppliers which they prove gives better results than support vector machines and other types of neural networks.

Indeed, fuzzy neural networks are proven to be very appropriate for supplier selection, that is probably due to the nature of the criteria used for the evaluation of suppliers.

3) Production

Lead time forecasting or predicting the manufacturing time

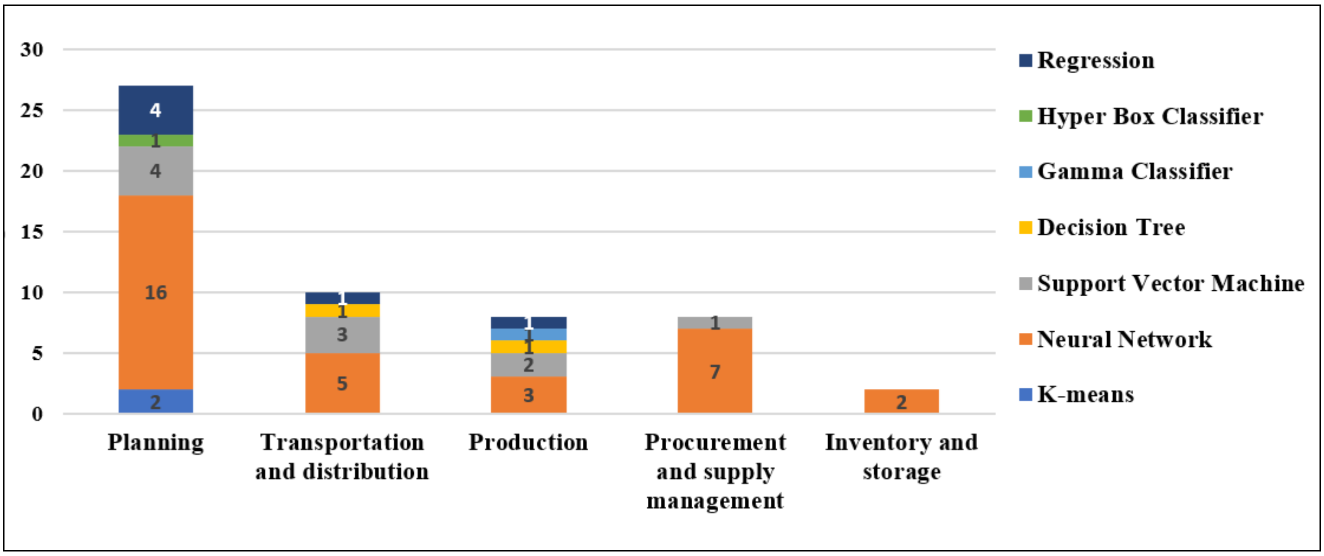

Fig. 2. The machine learning algorithms applied in each area of the supply chain

before the start of the manufacturing, can help in avoiding delays of a customer's delivery [12]. An example of machine learning for lead time forecasting employs support vector machines to analyze the factors that have influence over the lead time of batches of components of aerospace engines, and estimate whether a batch is going to be finished on the forecasted time [12].

Other examples of machine learning applications in a production context are as follows : Reference [18] apply a neural network and a Gamma classifier and compare them for the prediction of future oil production. Reference [43] model sugarcane yield via support vector machine, random forest, regression tree, neural networks, and Boosted Regression Trees, with random forests giving the best results. And, reference [44] apply self-organized maps to component selection of a green supply chain by grouping green products in order to unify production and reduce production costs.

4) Inventory and storage

Inventory refers to the idle resources that are required to ensure customer service. Storage incurs in important costs. For instance, according to [45], the annual cost of the storage of a single unit of inventory can range between 15% to 35% of its value. Thereby, a supply chain's success depends on its ability to control and plan inventory at minimum cost, all the while ensuring customer satisfaction. Reference [46] propose ANFIS for effective multi-echelon inventory management. It is used for demand and lead time forecasting, and is evaluated using performance metrics from the SCOR model. Another application is apply neural networks to predict the dwell time of import containers (the total time a container spends in one or more terminal stacks) in container terminals [47].

5) Transportation and distribution

The most popular application of machine learning in this particular area is the vehicle routing problem, dealing with the optimal routes for a vehicle to travel in order to deliver a product to the corresponding customers. Reference [20] address this problem using a simple neural network and compare its performance against human decisions and various routing heuristics in the literature, they found that neural networks performance is 48% better than that of the best routing heuristic. Reference [48] on the other hand employ ANFIS trained by a simulated annealing algorithm for solving it. Multiple researchers use machine learning to properly extract meaning from radio frequency identification (RFID) - used for the automatic identification, tracking and tracing of goods throughout the supply chain [49]- readings. For instance, reference [50] predicts the missing humidity and temperature sensor data in a RFID traceability system of a food supply chain, while [49] demonstrate that the support vector machine detects false-positive RFID readings with a higher accuracy than the decision tree and logistic regression.

Other applications include predicting the traffic flow of a distribution network using support vector machines [51], detecting anomalies and predicting diversions in airplane flights [11], and distributor selection [52] by combining between fuzzy logic and neural networks in a fuzzy Adaptive Resonance Theory neural network.

We notice that neural networks are the most used algorithm in all the stages of the supply chain. Which is understandable since neural networks can model the most complex linear and nonlinear problems. In fact, multi-layer perceptron, a type of neural network, have been proven to be a universal approximator capable of approximating any function [53], [54].So, neural networks are suitable to model different problems in the various areas of the supply chain, whether it's a regression, classification or even a clustering problem. Support vector machines, however, are mostly suitable for classification problems. While linear regression is most appropriate for simple linear problems where the use of more advanced techniques such as neural networks is too computationally expensive.

Indeed, machine learning algorithms are demonstrated to be significantly better at learning and forecasting all kinds of supply chain activities in comparison to other traditional techniques like the moving averages, the autoregressive integrated moving average, the exponential smoothing, grey theory, naïve forecasting, etc. [25][32][21][49][52].

V. The synthesis of Applications of Neural networks in supply chains

Neural networks are of many types, categorized mainly into two groups, the feed-forward networks and the recurrent networks.

The Feed-Forward Neural Networks are simple networks where there are no loops, information flows from one layer to the next, starting with the input layer, through the hidden layers for intermediate computations, and finally to the output layer.

The Recurrent Neural Networks (RNN) are networks where data flows in both directions creating loops, there are feedback connections in which outputs are fed back to the network as inputs. So, the result of a recurrent network for a step t-1 in time affects its result an instant later at the step t.

Fig. 3 shows that the multi-layer perceptron (MLP) is by far the most utilized neural network in all the stages. It is a feed-forward network that was developed to surpass the limits of the simple perceptron. It improved upon the perceptron by adding between the input and output layers some hidden layers which enable it to model nonlinear problems too. The MLP is a mathematical function that maps a set of input values to output values, this function is formed by composing many simple functions.

Other useful networks are the neuro-fuzzy networks that use fuzzy logic to model uncertainty, such as the Fuzzy Adaptive Resonance Theory neural network (FART) and the Adaptive Neuro-Fuzzy Inference System (ANFIS).

The Fuzzy Adaptive Resonance Theory neural network was introduced by Carpenter and Grossberg in 1991 [58] and is based on the Adaptive Resonance Theory which was introduced as a theory of human cognitive information processing by Grossberg [59], this theory has aided in the evolution of a series of neural network models for unsupervised category learning and pattern recognition.

The ANFIS was introduced by Jang in 1993 to model uncertain systems [60]. They are a hybrid model that combines an adaptive network and a fuzzy inference system, the adaptive network consists of a feed-forward neural network, while the fuzzy inference system is a system that applies a set of fuzzy logic rules to a knowledge base to infer new knowledge [60]. Indeed, the ANFIS model and the fuzzy ART are used in the supply chain to model uncertainty and randomness using fuzzy logic [52][22][34][40][41][45][49].

The self-organizing maps (SOM) however are neural networks used in unsupervised learning [61]. They can be used for data clustering or classification, vector projection and a variety of other purposes [38]. They have been used in supply chains to cluster products, suppliers, and customers [38], [44], [62].

The Boltzmann Machine (BM) and the time delayed neural network (TDNN) offer a time dimension.

The Boltzmann Machine is composed of primitive computing units interconnected with bidirectional links, each unit is in one of two states, on or off, it adopts these states as a probabilistic function of the states of its neighboring units [63]. Reference [28] applied an extension of the Boltzmann Machine: the Restricted Boltzmann Machine (RBM), it is a version where there are no connections between the units of a same hidden layer.

The time delayed neural network was introduced by [64] in 1989. It is a feed forward neural network where the basic units are modified by adding delays [64].

Other networks used in the supply chain literature include the Bayesian neural networks (BNN) where the output is probabilistic in nature, and the Radial Basis Function networks (RBF) which are two-layer neural networks with only one hidden layer. The RBF uses as activation functions the Radial Basis functions, usually Gaussian transfer functions, in the hidden layer and the sigmoid or linear functions in the output [65].

VI. Conclusion

In an era focused more and more on information and data, machine learning is a real asset from which enterprises can benefit greatly, including supply chains. Indeed, we show that machine learning algorithms are used in the upstream and downstream activities in all stages of the supply chain, but mainly in the planning and transportation activities. The majority of studies resort to neural networks because of their ability to model prediction, classification, and clustering problems. Followed by support vector machines which are very appropriate for classification problems. Followed by regression which is useful for linear problems.

Of all the previously discussed algorithms, neural networks are generally the most used and useful models. Especially, the multi-layer which were demonstrated to be able to model the most complex problems. Other well-known networks include ANFIS which is used to tackle fuzziness and uncertainty, and the recurrent neural networks that offer time dimension.

However, in the forty-two selected articles for this review, only one addressed deep learning by applying the Boltzmann Machine to predict energy consumption. As such, Deep Learning, a subset of machine learning, is not explored much in the domain of the supply chain.

So, for future work we would like to explore Deep learning for deriving value from social media data in order to capture the customer behavior in a supply chain.

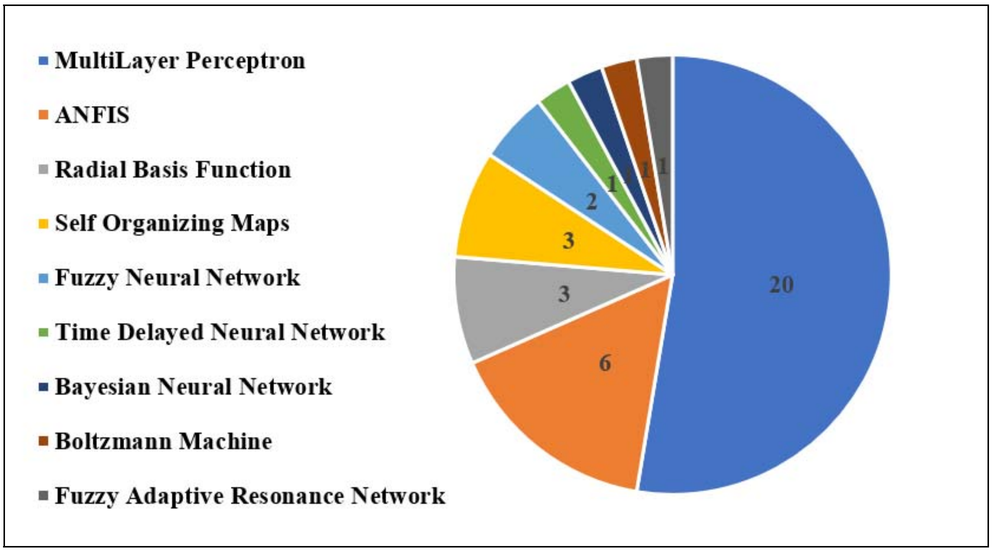

Fig. 3. The number of applications in the selected papers for each type of neural network

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