EXPLORING MACHINE LEARNING APPLICATIONS IN SUPPLY CHAIN MANAGEMENT

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ABSTRACT

In the current technological era, the rise of disruptive innovations is affecting the way industries run their operations. The disruptive impact of digitalization processes and the highly constant growth of sensible data are changing the very fabric of supply chain management. Disruptive technology offers innovative ways to tackle some of the main traditional approaches in the supply chain. Machine learning, which is viewed as disruptive technology, recently has evolved rapidly to optimize the process and efficiency in supply chain management. Machine learning could be applied in several stages of supply chain management from planning to the distribution process. In this paper, we explored and examined the literature of multiple machine learning algorithms and their application in the supply chain management, focusing on the demand forecasting stage since this the first and most important step of supply chain management. A total of 57 articles related to machine learning and demand forecasting were retrieved from ScienceDirect, Taylor and Francis, and Emerald databases. The result showed that the machine learning algorithm performs better than the traditional demand forecasting model. Moreover, neural network and support vector regression algorithms are among the most potential and applicable algorithms to implement in demand forecasting. The practical implication of this paper is in exposing the current machine learning issues in the industry to help stakeholders and decision-makers better plan corrective actions.

Keywords: disruptive technology, machine learning, supply chain management, demand forecasting

1. INTRODUCTION

In the current technological era, the rise of disruptive innovations is affecting the way companies run their businesses (Aamer, 2018). Disruptive innovation was introduced in 1995 and coined by the professor, entrepreneur, and author Clay Christensen (Bower & Christensen, 1996). In 2013, McKinsey Global Institute (MGI) has identified tweleve technology areas that exhibit the greatest economic impact and potential to disrupt by 2025. Those technology areas are mobile internet, automation of knowledge work (artificial intelligence and machine learning), Internet of Things (IoT), cloud technology, advanced robotics, autonomous and near-autonomous vehicles, next-generation genomics, energy storage, 3-D printing, advanced materials, advanced oil and gas explorations, and renewable energy (Manyika, et al., 2013). Those disruptive technologies have the potential to impact growth, employment and inequality in the market (Leipziger & Dodev, 2016). In general, the main objective of the supply chain is increase the product or service value that the customer is willing to pay for (Aamer, 2018; Aamer, 2017; Aamer & Islam, 2019; Aamer & Sawhney, 2004) . This challenge makes it inevitable that the company will need to improve the supply chain process efficiently. One method for which is having a good forecast of customer demand (Chong, Han, & Park, 2017). This will also decrease a common challenge for companies: the Bullwhip effect (Aamer, 2018b). To improve or maximize the total generated value, disruptive technologies influence the development of new techniques, principles, and models in supply chain management of the industries (Ivanov, Dolgui, & Sokolov, 2018). Machine learning, which is viewed as disruptive technology, recently has evolved rapidly to optimize the process and efficiency for supply chain management. With the ability for machine learning to automatically develop from the previous data set, machine learning could be applied in several stages of supply chain management (Bousqaoui, Achchab, & Tikito, 2017), including a demand forecast. It's especially the wide availability of big data for the company (Ragueseo, 2018) that can be used in machine learning to make a better forecast model. Various algorithms are used for machine learning, generally dividedinto two categories: supervised and unsupervised machine learning algorithms. This paper discusses and reviews various machine learning algorithms implemented on the supply chain, especially on-demand forecasting based on the literature.

2. METHODOLOGY

The methodology utilized in this paper is based on the Preferred Reporting Items for Systematic Protocol Review and Meta-Analysis (Moher, Liberati, Tetzlaff, Altman, & Th PRISMA Group, 2009). The content-analysis based literature review was carried out using the following steps. A search for articles in the ScienceDirect, Emerald and Taylor & Francis was used in this paper. The following search strings were used: *(Machine learning OR linear regression OR neural network OR support vector machine OR deep learning) AND (demand forecasting OR load forecasting)*, which matches the keyword string available in the title OR abstract OR keywords of previous studies. The retrieved papers were screened through steps. First of all, papers are reviewed on their titles and abstracts. Then the next screening consists of the following steps: i) papers that included any of the keywords were considered; ii) papers that proposed a new model of demand forecasting were considered; iii) papers only from journals were considered with conference papers excluded. After that, a brief content analysis was used to review all preselected papers one more time to closely look at the implementations and challenges of machine learning in supply chain management and demand forecasting. Figure 1 depics the systematic literature review process used in this paper.

3. RESULT AND DISCUSSION

The sampling process yielded 57 articles for review. Figure 2 shows that the number of papers published every year is increasing. This indicates the interest in researching machine learning for demand forecasting is increasing in popularity. The distribution of the papers reviewed is presented in Figure 3. Only 3 out of 57 articles discussed the implementation of machine learning for demand forecasting in the agriculture business sector and industry business sector got the most publications. The detail of the reviewed articles is presented in Table 1, which displays a summary of the machine learning algorithms used in the reviewed articles.

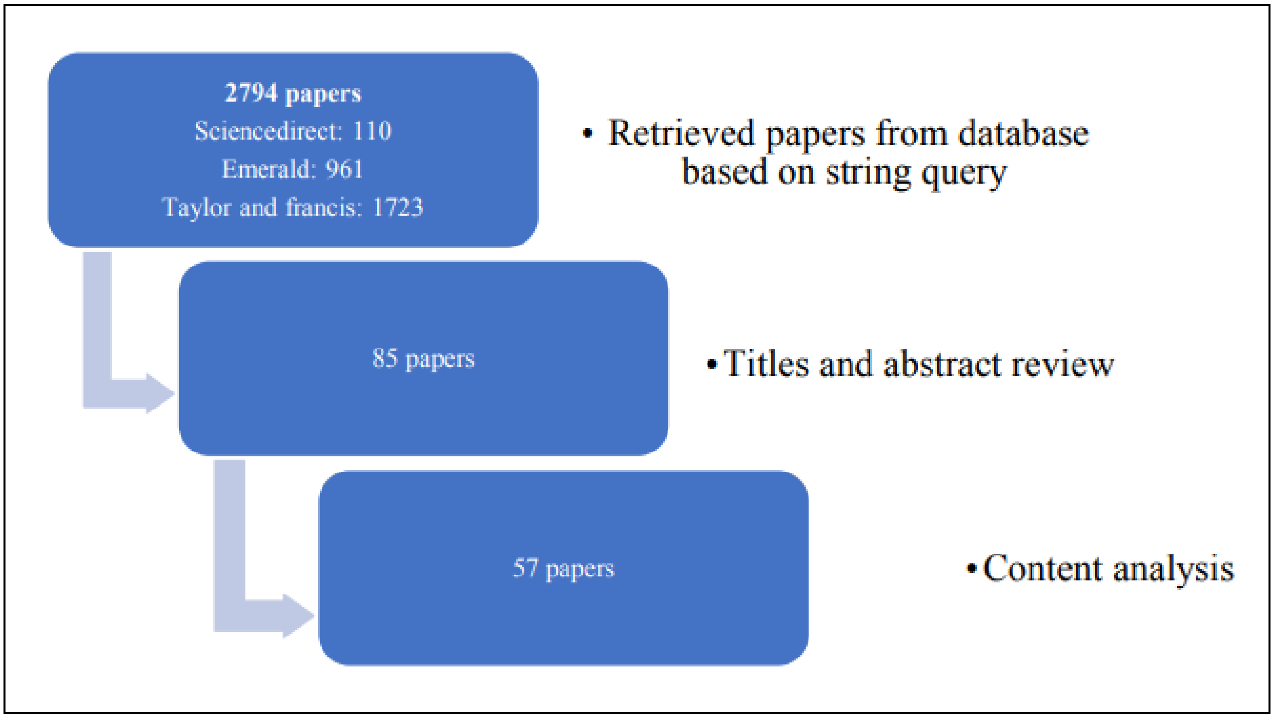

Figure 1. The systematic literature review processes.

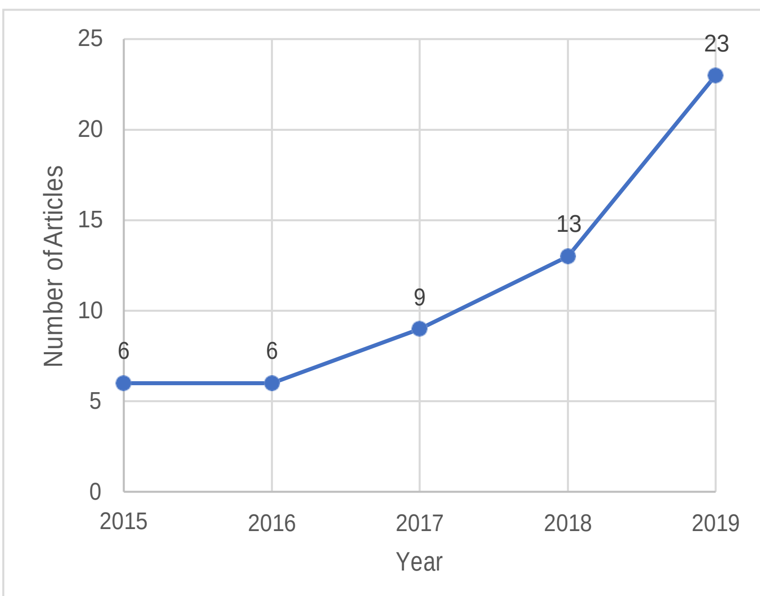

Figure 2. Number of papers published since 2015.

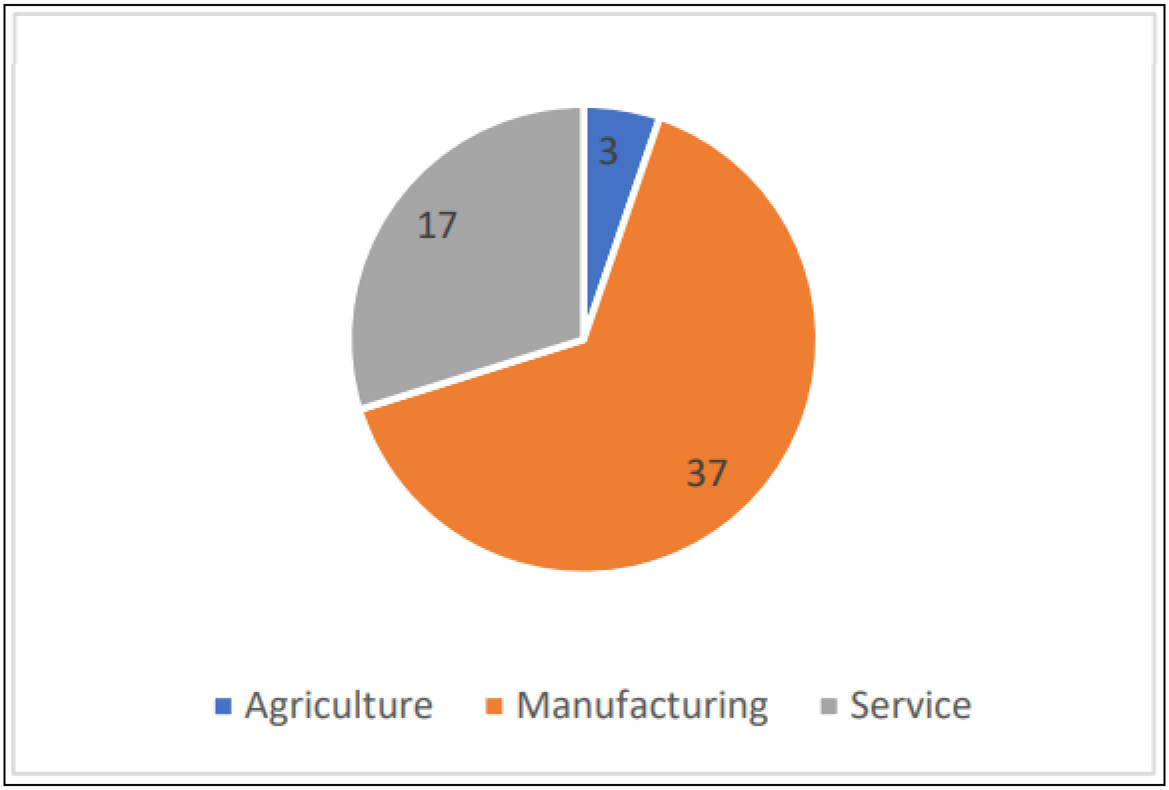

Figure 3. Publications distribution by business sectors

According to the summarized data in Table 1, the reviewed articles, which discuss machine learning applications in demand forecasting, focused on the implementation of machine learning. Performance review of various machine learning algorithms proposed the new demand forecasting models-based machine learning algorithms. Izadyar et al. (2015) compared various machine learning algorithms for heat demand including artificial neural networks extreme machine learning and genetic propagation algorithms. Their result showed that an extreme machine-learning algorithm had better performance in terms of accuracy. Huang, et al. (2019) also discussed machine learning algorithms for energy demand forecasting. The authors compared XGBoost, extreme learning machine, linear regression and support vector regression, and found support vector regression was the best algorithm among others. In terms of the proposed new algorithm, Ratree & Siriporn (2016) proposed a hybrid novel forecasting model, a combination between discrete wavelet decomposition (DWD) and a nonlinear autoregressive neural network. The proposed method was proficiently competent to improve the effectiveness of demand-side management activities. Mouatadid & Adamowski (2017) and Brentan et al. (2017) implemented support vector regression to forecast water demand in the short-term. Their proposed method allowed for real-time prediction. Mukesh & Jan (2015) and Al-Musaylh et al. (2018) proposed a neural network for water demand forecasting suitable for a long-term period. In general, reviewed articles claimed that machine learning could provide more accurate, faster, and easier demand forecasting when compared to the traditional forecasting models.

Table 1. Summary of publications by machine learning algorithms

Machine Learning Algorithm	References	Number of Articles
Neural Network	(Puchalsky, Ribeiro, Veiga, Freire, & Coelho, 2018), (Wen, Zhou, Yang, & Lu, 2019), (Liu, Xu, Guo, & Chen, 2019), (Mason, Duggan, & Howley, 2018), (Sharifzadeh, Cikinioti-Lock, & Shah, 2019), (Rahman, Srikumar, & Smith, 2018), (Mukesh & Jan, 2015), (Sala-Caardoso, Delgado-Prieto, Kampouropoulos, & Romeral, 2018), (Rahman & Smith, 2018), (Hribar, Potocnik, Silc, & Papa, 2019), (Golshani, Shabanpour, Mohmoudifard, Derrible, & Mohammadian, 2018) (Yao, et al., 2018), (Claveria, Monte, & Torra, 2016), (Ratree & Siriporn, 2016) & (Xu, Ji, & Liu, 2018)	15
Support Vector Regression	(Dong, Li, Rahman, & Vega, 20161), (Huang, et al., 2019`), (Maldonado, Gonzalez, & Crone , 2019), (Al-Musaylh, Deo, Adamowski, & Li, 2018), (Yildiz, Bilbao, & Sproul, 2017), (Brentan, Jr., Herrera, Izquierdo, & Garcia, 2017), (Ahmad, Chen, & Shair, 2018), (Beyca, Ervural, Tatoglu, Ozuyar, & Zaim, 2019) & (Plakandaras, Papadimitriou, & Gogas, 2019)	9
Extreme Learning Machine	(Munoz-Bulnes, Portilla-Figueras, Salcedo-Sanz, & Ser, 2015), (Wu, Cui, Chen, Kong, & Wang, 2019), (Ertugrul, 2016), (Hassan, Khosravi, Jaafar, & Khanesar, 2016), (Mouatadid & Adamowski, 2017), (Izadyar, Ong, Shamshirband, Ghadamian, & Tong, 2015) & (Sun, Wei, Tsui, & Wang, 2019)	7
Random Forest	(Ahmad & Chen, 2019), (Johannesen, Kolhe, & Goodwin, 2019), (Qiu, Zhang, Suganthan, & Amaratunga, 2017), (Duerr, et al., 2018), (Cheng, Chen, Vos, Lai, & Witlox, 2019), (Ferrara, Liberto, Nigro, Trojani, & Valenti, 2019) & (Tanizaki, Hoshino, Shimmura, & Takenaka, 2018)	7
Support Vector Machine	(Bolandnazar, Rohanii, & Taki, 2019), (Candelieri, et al., 2019), (Allawi, Jaafar, Hamzah, & El-Shafie, 2019), (Wang, Chen, & Bi, 2015) & (Cao, Jiang, & Wang, 2016)	5
Artificial Neural Network	(Mouatadid S. , Adamowski, Tiwari, & Quilty, 2019), (Chen & Ahmad, 2019), (Saxena, Aponte, & McConky, 2019) & (Claveria, Monte, & Torra, 2015)	4
Deep Learning	than, & Amaratunga, 2017), (Lv, Peng, & Wang, 2018) & (Ke, Zheng, Yang, & Chen, 2017)	3
Linear Regression	(Ciulla & D'Amico, 2019) & (Dhamija, Yadav, & Jain, 2017)	2
Back Propagation Network	(Gao & Lee, 2019)	1
Bayesian Network	(Bassamzadeh & Ghanem, 2017)	1
Fuzzy Inductive Reasoning	(Jurado, Nebot, Mugica, & Avellana, 2015)	1
Genetic Algorithm	(Hu, 2017)	1
k-Nearest Neighbor	(Rice, Park, Pan, & Newman, 2019)	1

Based on the data presented above, the most used machine learning algorithm from the reviewed publications was the neural network algorithm. Some articles also reviewed and compared this algorithm with other algorithms and showed that the neural network algorithm performs better. As an example, (Liu, Xu, Guo, & Chen, 2019) compared neural networks with support vector machines for energy demand forecasting and (Hribar, Potocnik, Silc, & Papa, 2019) compared it with linear regression and extreme learning machine algorithms for natural gas demand prediction. Nonetheless, this does not mean that the neural network always performs better than the others in every situation. Machine learning algorithms could perform better in one situation but could perform worse in others, it depends on the given data and situation (Goodfellow, Bengio, & Courville, 2015).

5. CONCLUSION

This paper aimed to give an insight review of recent research in the area of machine learning and supply chain management, especially forecasting demand, based on a systematic literature review. We collected and reviewed 57 journal papers from 3 databases: ScienceDirect, Taylor and Francis, and Emerald. All the collected journal papers focused on the implementation of the machine learning algorithms in supply chainand and demand forecasting. According to the result, energy and electricity demand had the most published papers discussing machine learning. Various algorithms were proposed in the published and reviewed articles. Based on the data, the neural network machine learning algorithm is the most implemented in the reviewed articles. Moreover, reviewed articles show that the machine learning algorithms perform more accurately, faster and easier for demand forecasting when compared to traditional demand forecasting models.

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