Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting

Ammar Mohamed Aamer  
Faculty of Engineering & Technology  
Sampoerna University, Jakarta, 12780, Indonesia  
Email: ammar.aamer@sampoernauniversity.ac.id (Corresponding Author)

Luh Putu Eka Yani  
Faculty of Engineering & Technology  
Sampoerna University, Jakarta, 12780, Indonesia  
Email: eka.yani@sampoernauniversity.ac.id

I Made Alan Priyatna  
Faculty of Engineering & Technology  
Sampoerna University, Jakarta, 12780, Indonesia  
Email: alan.priyatna@sampoernauniversity.ac.id

ABSTRACT

In today’s fast-paced global economy coupled with the availability of mobile internet and social networks, several business models have been disrupted. This disruption brings a whole list of opportunities and challenges for organizations and the domain of supply chain management. Given big data availability, data analytics is needed to convert data into meaningful information, which plays an important role in supply chain management. One of the disruptive data analytics techniques that are predicted to impact growth, employment, and inequality in the market is automation of knowledge work, better known as machine learning. In this paper, we focused on comprehensively reviewing machine learning applications in demand forecasting and underlying its potential role in improving the supply chain efficiency. A total of 1870 papers were retrieved from Scopus and Web of Science databases based on our string query related to machine learning. A reduced total of 79 papers focusing on demand forecasting were comprehensively reviewed and used for the analysis in this study. The result showed that neural networks, artificial neural networks, support vector regression, and support vector machine were among the most widely used algorithms in demand forecasting with 27%, 22%, 18%, and 10%, respectively. This accounted for 77% of the total reviewed articles. Most of the machine learning application (65%) was applied in the industry sector, and a limited number of articles (5%) discussed the agriculture sector. This paper’s practical implication is in exposing the current machine learning issues in the industry to help stakeholders and decision-makers better plan transformation actions.

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

1. INTRODUCTION

Today’s advancement in technology, coupled with the availability of mobile internet and social networks, has disrupted several business models. This disruption brings a whole list of opportunities and challenges for organizations and the domain of supply chain management (Aamer, 2018; Bower & Christensen, 1996; Huddiniah & ER, 2019). In an attempt to improve the supply chain's total generated value, it is predicted that disruptive technologies would influence the development of new techniques, principles, and models in supply chain management of the industries (Ivanov et al., 2019). Some of the supply chain management domain opportunities include better visibility and traceability of products and services along the supply chain, and some of the challenges include cybersecurity, technology learning curves, and adaptability. Another important consequence of today’s technology, and the availability of mobile technology and the Internet of Things (IoT), is the increased data collection volume, which is referred to as big data. Big data is known by the five V’s: Volume, Velocity, Variety, Veracity, and Value (Affia et al., 2019; Jeble et al., 2018). Given big data availability, data analytics is needed to convert data into meaningful information, which plays an important role in supply chain management. Data analytics can be defined as using statistical and mathematical tools to analyze available data and produce meaningful information for decision-makers (Jeble et al., 2018).

One of the disruptive data analytics techniques that is predicted to impact growth, employment, and inequality in the market is automation of knowledge work, better known as machine learning (Leipziger et al., 2016; Manyika et al., 2015; Yani et al., 2019). Various algorithms are used in machine learning, which is generally divided into two categories: supervised and unsupervised machine learning algorithms. Machine learning, which is viewed as a disruptive technology, has rapidly evolved in recent years to optimize the process and efficiency in supply chain management. According to research, machine learning could be applied in several stages of supply chain management.
More specifically, it could be used to generate better forecasting models in the presence of big data (Bousqouai et al., 2018; Raguseo, 2018).

Supply chain management focuses on creating value for the customers by optimizing the flow of products and services through the supply chain effectively and efficiently (Aamer, 2018; Aamer and Sawhney, 2004; Chopra and Meindl, 2013; Sahara et al., 2019; Yani et al., 2019). However, one of the most dynamic issues in supply chain management is the quest of having reliable customer demand forecasting (Chong et al., 2017). One of the most common consequences of poor demand forecasting is known as the Bullwhip Effect (Norman and Naslund, 2019). Therefore, from the perspective of economic growth, employment, and inequality in the market is predicted to apply disruptive technology, such as machine learning, to supply chain management. To contribute to Indonesia’s optimistic and critical strategic plan toward industry revolution 4.0 by 2025 (BKPM, 2019), important tools needed in areas related to the Indonesian government strategic plan's focus sectors should be pinpointed. This research focused on comprehensively overviewing machine learning applications in demand forecasting and underlying its potential role in improving the supply chain efficiency. Even though there are other reviews on data analytics and machine learning, there are limited reviews on machine learning algorithms in demand forecasting. In this research, we provided an overview of machine learning application in demand forecasting for the supply chain by answering the following questions:

- RQ1: What are the machine learning algorithms and techniques used in demand forecasting in the supply chain?
- RQ2: What are the trends and gaps in the literature reviewed?

The remainder of this research is organized as follows: Section 2 presents background information about the study. Section 3 discusses the methodology used in this paper. In section 4, we present the overview results and discuss the literature gaps. Section 5 concludes the research with future research directions.

2. MACHINE LEARNING AND DEMAND FORECASTING

Research in operations and supply chain management has proved the importance and big role supply chain management plays in many organizations’ sustainability, especially in today’s disruptive era. For the past fifteen years, historical data has shown us that several organizations were forced out of business because of misreading the market signs and not being able to keep up with today’s rapid development in technology and rapid growth in consumer demand and expectations. For example, Blockbuster in the USA went out of business for not being able to keep up with the technology trend and reading consumer behavior and demand. Other successful world-class organizations, such as Walmart in the USA, still clinch the top ranking among companies in the USA for reasons including the efficient supply chain network and its management. Other similar organizations in the context of Asia in general, and Indonesia in particular, include organizations such as Tokopedia, an e-commerce company similar to Amazon in the USA, which leverage emerging technology in improving logistics, fulfillment, payment to anticipate and forecast consumer demand and have innovative supply chain management operations. One can claim that the more efficient, transparent, resilient, and responsive the supply chain, the better revenue, and profit the organization can reap.

One critical factor of supply chain management efficiency is the accuracy of demand forecasting, as it plays an essential role in reducing the Bullwhip Effect (Chong et al., 2017). Therefore, there is a need to develop reliable demand forecasting models to make better and more accurate predictions. Machine learning is one promising disruptive tool that could be utilized in developing better demand forecasting models than what is being used in supply chain management currently. Machine learning is a subset of artificial intelligence where the machine learning algorithm acts or performs the task without being explicitly programmed. The machine can learn automatically from the past raw data to generate predictive models based on predesigned algorithms. In general, there are two types of learning algorithms: supervised and unsupervised learning. Supervised machine learning algorithms learn from labeled data: input and output. The algorithm is responsible for finding the relationship between the input and the output and stops learning when it achieves an acceptable performance level.

On the other hand, there is only input data and no corresponding output data in unsupervised learning. The algorithm aims to find patterns and structure to learn more about the given data (Goodfellow et al., 2016). Supervised and unsupervised learning algorithms are used mainly for four types of tasks: regression, classification, clustering, and association (Kone and Karwan, 2011). Various algorithms are used for machine learning, including, among others, neural networks, support vector machines, regression, decision trees, random forests, and k-means algorithms. Each algorithm has its advantages and disadvantages in implementation, depending on the case of the business. It is not in the scope of this research to discuss each machine learning topic but to overview which topic has been addressed in the context of demand forecasting.

Recently, machine learning has been utilized in different stages of supply chain management in the industry. Some of the most recent research addressed the application of machine learning, such as Bousqouai et al. (2018), Feki et al. (2016), Varela (2015), and Bonnes (2014). Others have specifically presented an overview of machine learning applications in demand forecasting, such as Carbonneau et al. (2008). Nonetheless, there is still a lack of focused overview studies of machine learning applications in the demand forecasting area. The following sections present a comprehensive overview of machine learning applications demand to forecast related to three main sectors in Indonesia. According to the World Bank, agriculture, industry, and service sectors are the top three of Indonesia’s business sectors (The World Bank, 2019). The agriculture sector includes forestry, hunting, fishing as well as cultivation of crops and livestock production. The industry sector includes mining, manufacturing, construction, electricity, water, and gas. Lastly, the services sector has businesses such as hotels and restaurant services, transport, government, financial, professional, and personal services such as education, healthcare, and real estate services. Indonesia is the second-
largest rubber producer in the world. Other major crops include sugarcane, rice, coffee, palm oil, and other crops that make up the agriculture business sector contribute 13.14% of the country’s GDP. Industry sectors such as the manufacturing of textiles, cement, electronic products, rubber tires, and others contribute around 39.37% of Indonesia’s GDP. Meanwhile, the service sector, such as financial institutions, transportations, communications, has a higher contribution among the other two sectors. The service sector contributes approximately 43.6% of the total Indonesian GDP (The World Bank, 2019).

3. METHODOLOGY

This paper aims to explore and consolidate the past and current findings in the implementation of machine learning for demand forecasting through a comprehensive analysis of the related literature. Given the literature review nature of this research, we followed the systematic literature review method in conducting our overview as it is more suitable and rigorous when using digital databases to retrieve, screen, and synthesize previous research (Okoli and Schabram, 2010; Webster and Watson, 2002). Our research strategy was carried out using the following search strings related to our research questions: (Machine learning OR linear regression OR neural network OR support vector machine OR deep learning) AND (demand forecasting), which match the keyword string available in the title OR abstract OR keywords of previous studies. The search for articles was limited to the last ten years, from 2010 to 2019. Our literature search was limited to only those databases, journals, and conferences with a good academic reputation. Due to the recent emergence of machine learning applications in supply chain management, we had to expand our searched databases to include reputable databases, journals, and conferences with credible and sound academic reputations. We used the Scopus and Web of Science databases as our sources for retrieving the relative studies.

In selecting the studies to be reviewed, we retrieved all papers written in English that met our search strings and keywords. The next step for screening consisted of papers that proposed any demand forecasting model. The final list of papers retrieved from the database on the string queries was 1870 papers as illustrated in Figure 1: 558 papers from Science direct, 316 papers from Emerald, 957 papers from Taylor & Francis, 34 papers from IEEE, and five papers from. After that, we conducted a screening process of the retrieved papers to search the title and abstract of 1870 papers to find if the papers addressed our research question of the implementations of machine learning and demand forecasting in supply chain management. Given many papers, we reviewed the titles and abstracts as a more efficient screening process, and the total was reduced to 124 related studies. We conducted a more systematic content analysis of the most relevant and remaining total of 77 papers.

Figure 1 The systematic literature review processes

4. RESULTS AND DISCUSSION

The total number of published papers in the last ten years in machine learning and demand forecasting has fluctuated. However, there is a noticeable and relatively significant increase in the previous two years, as depicted in Figure 2. 34 papers published in 2018 and 2019 alone counted for 44% of the total publications in the last ten years. Another important finding is that most of the published papers in machine learning and demand forecasting focused on the industry sector with 65% and followed by the service and agriculture with 30% and 5%, respectively. The summary results of our review are presented in Table 1 and Table 2. Table 1 shows the distribution of published papers by sector and the Machine Learning algorithm used. Table 2 further summarizes the distribution of articles by the type of machine learning algorithm used.

Figure 2 The trend of published papers in machine learning applications in demand forecasting
| Machine Learning Algorithm | References | Total # of Papers | % of Algorithm | % Sub-sector | % Sector |
|----------------------------|------------|-------------------|----------------|-------------|----------|
| Agriculture Sector         |            |                   |                |             |          |
| Support Vector Machine     | (Bolandnazar et al., 2019; Du et al., 2013; Zhu et al., 2019) | 3                | 75%            |             |          |
| Artificial Neural Network  | (Puchalsky et al., 2018) | 1                | 25%            |             |          |
| Energy Demand              |            | 51                | 65%            |             |          |
| Artificial Neural Network  | (Bekkari and Zeddouri, 2019; Kialashaki and Reisel, 2014; Saloux and Candanedo, 2018) | 3                | 25%            |             |          |
| Neural Network             | (Ahmad and Chen, 2018; Mason, Duggan, Barrett, et al., 2018) | 2                | 17%            |             |          |
| Decision Tree              | (Saloux & Candanedo, 2018) | 1                | 8%             |             |          |
| Linear Regression          | (Spencer and Al-Obeidat, 2016) | 1                | 8%             |             |          |
| Random Forest              | (Huang, Liang, et al., 2019) | 1                | 8%             |             |          |
| Reinforcement Learning     | (Wee and Nayak, 2019) | 1                | 8%             |             |          |
| Support Vector Machine     | (Saloux and Candanedo, 2018; Shi et al., 2012) | 2                | 17%            |             |          |
| Support Vector Regression  | (Chou and Ngo, 2016) | 1                | 8%             |             |          |
| Electricity Demand         |            | 20                | 39%            |             |          |
| Artificial Neural Network  | (Badri et al., 2012; Chu et al., 2011; Çunkaş and Altun, 2010; Ertugrul, 2016; Eseye et al., 2019; Saxena et al., 2019) | 6                | 30%            |             |          |
| Support Vector Regression  | (Al-Musayyf et al., 2018; Elattar et al., 2010; Malbonado et al., 2019; Nagi et al., 2011) | 4                | 20%            |             |          |
| Deep Learning              | (Qiu, Zhang, et al., 2017) | 1                | 5%             |             |          |
| Extreme Learning Machine   | (Liu et al., 2019) | 1                | 5%             |             |          |
| Random Forest              | (Johannesen et al., 2019) | 1                | 5%             |             |          |
Table 2: Article distribution by industry sector and machine learning algorithm used (cont’)

| Machine Learning Algorithm | References | Total # of Papers | % of Algorithm | % Sub-sector | % Sector |
|----------------------------|------------|-------------------|----------------|--------------|----------|
| Support Vector Machine     | (Huang, Liang, et al., 2019) | 1 | 5% |             |          |
| Gaussian Process            | (Alamaniotis et al., 2012) | 1 | 5% |             |          |
| Neural Network              | (Hanmandlu and Chauhan, 2011; Khosravi and Nahavandi, 2014; Lou and Dong, 2013; Nose-Filho et al., 2011; Quan et al., 2014) | 5 | 25% |             |          |
| Water Demand                |             | 9 | 18% |             |          |
| Artificial Neural Network   | (Kofinas et al., 2014; Vijai and Bagavathi Sivakumar, 2018) | 2 | 22% |             |          |
| Extreme Learning Machine   | (Mouatadid and Adamowski, 2017) | 1 | 11% |             |          |
| Neural Network              | (Tiwari and Adamowski, 2017a) | 1 | 11% |             |          |
| Support Vector Regression   | (Braun et al., 2014; Brentan et al., 2017; Herrera et al., 2010, 2011) | 4 | 44% |             |          |
| Support Vector Machine      | (Candelieri et al., 2015) | 1 | 11% |             |          |
| Natural Gas Demand          |             | 3 | 6%  |             |          |
| Extreme Learning Machine   | (Izadyar et al., 2015) | 1 | 33% |             |          |
| Neural Network              | (Hribar et al., 2019) | 1 | 33% |             |          |
| Support Vector Regression   | (Beyca et al., 2019) | 1 | 33% |             |          |
| Cellular Network Demand     |             | 1 | 2%  |             |          |
| Deep Learning               | (Fang et al., 2018) | 1 | 100% |             |          |
| Apparel Industry Demand     |             | 2 | 4%  |             |          |
| Artifical Neural Network    | (Aksoy et al., 2012, 2014) | 2 | 100% |             |          |
| Heat Demand                 |             | 1 | 2%  |             |          |
| Neural Network              | (Sala-Cardoso et al., 2018) | 1 | 100% |             |          |
Table 3 Article distribution by industry sector and machine learning algorithm used (cont’)

| Machine Learning Algorithm | References | Total # of Papers | % of Algorithm | % Sub-sector | % Sector |
|-----------------------------|------------|-------------------|----------------|--------------|----------|
| Electronics Demand          |            | 1                 |                | 2%           |          |
| Neural Network              | (Chen, Yeh, et al., 2012) | 1                 | 100%           |              |          |
| Residential Demand          |            | 1                 |                | 2%           |          |
| Neural Network              | (Percy et al., 2018) | 1                 | 100%           |              |          |
| Coal Demand                 |            | 1                 |                | 2%           |          |
| Artificial Neural Network   | (Jebaraj et al., 2011) | 1                 | 100%           |              |          |
| Services Sector             | 24         |                   |                | 30%          |          |
| Tourism Demand              | 11         |                   |                | 46%          |          |
| Neural Network              | (Claveria et al., 2015; Huang et al., 2012; Yao et al., 2018; Yu et al., 2017) | 4 | 36% |              |
| Artificial Neural Network   | (Golshani et al., 2018; King et al., 2014) | 2 | 18% |              |
| Extreme Learning Machine    | (Sun et al., 2019) | 1 | 9% |              |
| k-Nearest Neighbor          | (Rice et al., 2019) | 1 | 9% |              |
| Random Forest               | (Cheng et al., 2019) | 1 | 9% |              |
| Gaussian Process            | (Wu et al., 2012) | 1 | 9% |              |
| Support Vector Regression   | (Hong et al., 2011) | 1 | 9% |              |
| Transportation Demand       | 9          |                   |                | 38%          |          |
| Support Vector Regression   | (Plakandaras et al., 2019; Zhao and Mi, 2019) | 2 | 22% |              |
| Adaptive-neuro-fuzzy classifier | (Minal et al., 2019) | 1 | 11% |              |
| Back Propagation Network    | (Gao and Lee, 2019) | 1 | 11% |              |
| Deep Learning               | (Ke et al., 2017) | 1 | 11% |              |
Table 4 Article distribution by industry sector and machine learning algorithm used (cont’)

| Machine Learning Algorithm | References | Total # of Papers | % of Algorithm | % Sub-sector | % Sector |
|----------------------------|------------|-------------------|----------------|-------------|---------|
| Neural Network             | (Chen, Kuo, et al., 2012; Xu et al., 2018; Ye et al., 2012) | 3 | 33% |             |         |
| Random Forest              | (Ferrara et al., 2019) | 1 | 11% |             |         |
| Healthcare Service Demand  |            | 3 | 13% |             |         |
| Neural Network             | (Jiang et al., 2018) | 2 | 67% |             |         |
| XGBoost                    | (Klute et al., 2019) | 1 | 33% |             |         |
| Banking Service Demand     |            | 1 | 4%  |             |         |
| Neural Network             | (Joseph et al., 2013) | 1 | 100% |             |         |
| Service-Oriented Manufacturing Demand | | 1 | 4%  |             |         |
| Support Vector Machine     | (Cao et al., 2017) | 1 | 100% |             |         |

Table 2 Distribution of articles by machine learning algorithm used

| Machine Learning Algorithm | References                                                                 | Number of Articles | % From Total |
|----------------------------|----------------------------------------------------------------------------|--------------------|--------------|
| Neural Network             | (Ahmad et al., 2018; Chen, Yeh, et al., 2012; Chen, Kuo, et al., 2012; Claveria et al., 2016; Hanmandlu and Chauhan, 2011; Hribar et al., 2019; Huang et al., 2012; Jiang et al., 2018; Joseph et al., 2013; Khosravi and Nahavandi, 2014; Lou and Dong, 2013; Mason, Duggan and Howley, 2018; Nose-Filho et al., 2011; Percy et al., 2018; Quan et al., 2014; Sala-Cardoso et al., 2018; Tiwari and Adamowski, 2017b; Xu et al., 2018; Yao et al., 2018; Ye et al., 2012; Yu et al., 2017) | 21 | 27% |
| Artificial Neural Network  | (Aksoy et al., 2012, 2014; Badri et al., 2012; Bekkari and Zeddouri, 2019; Chu et al., 2011; Çunkaş and Altun, 2010; Ertugrul, 2016; Eseye et al., 2015; Golshani et al., 2018; Jебaraj et al., 2011; Kialashaki and Reisel, 2014; King et al., 2014; Kofinas et al., 2014; Puchalsky et al., 2018; Saloux and Candanedo, 2018; Saxena et al., 2019; Vijai and Bagavathi Sivakumar, 2018) | 17 | 22% |
| Support Vector Regression  | (Al-Musayih et al., 2018; Beyca et al., 2019; Braun et al., 2014; Brentan et al., 2017; Chou and Ngo, 2016; Elattar et al., 2010; Herrera et al., 2010, 2011; Hong et al., 2011; Maldonado et al., 2019; Nagi et al., 2011; Plakandaras et al., 2019; Zhao and Mi, 2019) | 13 | 17% |
Table 2 Distribution of articles by machine learning algorithm used (cont’)

| Machine Learning Algorithm            | References                                                                 | Number of Articles | % From Total |
|---------------------------------------|---------------------------------------------------------------------------|--------------------|--------------|
| Support Vector Machine                | (Bolandnazar et al., 2019; Candelieri et al., 2015; Cao et al., 2017; Du et al., 2013; Huang, Liang, et al., 2019; Saloux and Candanedo, 2018; Shi et al., 2012; Zhu et al., 2019) | 8                  | 10%          |
| Extreme Learning Machine             | (Izadyar et al., 2015; Liu et al., 2019; Mouatadid and Adamowski, 2017; Sun et al., 2019) | 4                  | 5%           |
| Random Forest                        | (Cheng et al., 2019; Ferrara et al., 2019; Huang, Yuan, et al., 2019; Johannesen et al., 2019) | 4                  | 5%           |
| Deep Learning                        | (Fang et al., 2018; Ke et al., 2017; Qiu, Ren, et al., 2017) | 3                  | 4%           |
| Adaptive-neuro-fuzzy classifier      | (Minal, Sekhar, & Madhu, 2019) | 1                  | 1%           |
| Back Propagation Network             | (Gao & Lee, 2019)                                                   | 1                  | 1%           |
| Decision Tree                        | (Saloux & Candanedo, 2018)                                           | 1                  | 1%           |
| Gaussian Process                     | (Alamaniotis et al., 2012)                                           | 1                  | 1%           |
| k-Nearest Neighbor                   | (Rice et al., 2019)                                                 | 1                  | 1%           |
| Linear Regression                    | (Spencer & Al-Obeidat, 2016)                                         | 1                  | 1%           |
| Reinforcement Learning               | (Wee & Nayak, 2019)                                                 | 1                  | 1%           |
| XGBoost                               | (Klute et al., 2019)                                                | 1                  | 1%           |
| Total                                 |                                                                       | 78                 | 100%         |

According to Table 1, most of the research presented in the literature focused on applying machine learning algorithms in the industry sector, especially for the electricity and energy demand with 39% and 24%, respectively. A minimal number of papers addressed the demand forecasting in the manufacturing category, such as the apparel industry (4%) and electronics (2%), which accounted for the least percentage. This could be due to the difficulty facing manufacturers in adopting new technologies and presents a gap in the literature that needs to be further investigated. Artificial neural networks and neural networks are the most used algorithms among all industry sub-sectors, with percentages ranging between 17% and 100%, as presented in Table 1. This supports the claim of authors that artificial neural networks and neural networks offer better demand forecasting accuracy. They are also supported by the total number of articles in Table 2. Table 2 shows that both artificial neural networks and neural networks accounted for 48% of the machine learning applications' algorithms in demand forecasting for the last ten years.

With the increased technology applications and widespread e-services, we see evidence of increased utilization of machine learning in this sector. According to our review, the service sector came in second place after the industry sector, with a total percentage of 30% from the general application of machine learning in demand forecasting in the supply chain. More machine learning algorithms are evident in the tourism and transportation subsectors with a large total percentage of 84%. Like the industry sector, neural and artificial networks were among the highest algorithms. Besides, support vector regression was used in demand forecasting. This could be to the fast-paced development of several online applications that offer services to customers where big data is collected and used to targeted demand forecasting and targeted marketing, especially in social media networks.

The lowest percentage of machine learning applications in demand forecasting is in the agriculture sector, with 5%. This is an alarming percentage for the low utilization of data analytics and machine learning algorithms in a critical and
important national economy industry. This could be due to the lower level of technology implementation and integration in the agriculture industry. This is one of the literature gaps that researchers and practitioners need to address to improve the agriculture sector, especially in countries such as Indonesia, where this sector plays a significant role in the country’s economic development.

The list of machine learning algorithms and techniques used in demand forecasting in the supply chain are presented in Table 2. The top algorithms used in demand forecasting, based on our review, were neural network, artificial network, support vector regression, and support vector machine with 27%, 22%, 18%, and 10%, respectively. This accounted for 77% of the total reviewed articles. The remaining algorithms ranged between 1% and 5%, which indicated the unpopularity of these algorithms in each of the three main sectors and their subsectors. This is in no way an indication of these algorithms’ un-applicability in demand forecasting but merely the popularity of what has been applied. Some researchers conducted a comparative analysis for some of the least popular machine learning algorithms to give some insight into the suitability and applicability of these algorithms. For example, Izadyar et al. (2015) compared several machine learning algorithms such as artificial neural networks, neural networks, and extreme machine learning. The authors claimed stated that an extreme machine learning algorithm has better performance in terms of accuracy. Similarly, Huang et al. (2019) compared XGBoost, extreme learning machine, linear regression, and support vector regression and found that the support vector regression algorithm produced more accurate results, among others. This calls for further investigation of the least popular algorithms and their applicability in the sectors and perhaps other sectors.

We can conclude that machine learning algorithms could provide better accuracy and less computational cost for demand forecasting than traditional forecasting models. This finding is supported by some of the reported studies in the literature, including Golshani et al. (2018), Jiang et al. (2018), Saloux & Candanedo (2018), Cheng et al. (2019), Saxena et al. (2019). Besides, based on our review, one of the trends in the machine learning applications in demand forecasting included is the application of neural network algorithms when using machine learning in demand forecasting in the context of supply chain management. This could be due to better neural network performance in forecasting accuracy compared to other algorithms such as linear regression and extreme learning machine algorithms. This is by no means an indication that neural network algorithms in machine learning always outperform others. Machine learning algorithms could perform better in one situation but not in others, depending on data and situation (Goodfellow et al., 2016). Another trend is that most of the machine learning application is in the industry sector, and the gap is in the agriculture sector. This calls for more research needed in the agricultural area to improve data analytics’ efficiency by implementing machine learning in demand forecasting to enhance the efficiency of supply chains. This is important for economic growth for countries such as our country of interest, Indonesia, where both sectors contribute significantly to the national GDP.

5. CONCLUSION

This paper addressed two main questions related to machine learning applications and techniques used in demand forecasting in the supply chain. Also, we identified some of the associated trends and gaps in the machine learning literature review. Our study classified the applications based on three business sectors, namely, agriculture, industry, and service sectors. Based on our analysis, we concluded that machine learning algorithms could provide better accuracy and less computational cost for demand forecasting than traditional forecasting models. Also, based on our review, one of the trends in the machine learning applications in demand forecasting included is the application of neural network algorithms when using machine learning in demand forecasting in the context of supply chain management. Most of the machine learning applications were found in the industry sector, and limited machine learning applications were found in the agriculture sector. This calls for more research needed in the agricultural area to improve data analytics’ efficiency by implementing machine learning in demand forecasting to enhance the efficiency of supply chains. This is important for economic growth for countries such as our country of interest, Indonesia, where both sectors contribute to the national GDP.

Future research should also focus on applying machine learning in the service sector in both the transportation and health industry. Given the current global disruption of the supply chain and economy in general, due to the pandemic known as COVID-19, we believe that machine learning could play a significant role in creating more efficient and transparent collaborative planning, forecasting, and replenishment along the supply chain.

This study contributes to the supply chain management body of knowledge. It also serves as a foundational study to help other researchers address the research gap by expanding machine learning applicability in other vital sectors such as agriculture. The study also contributes practically to managers and decision-makers or organizations for what has been done to transition from traditional forecasting models and use machine learning algorithms to seek better and more accurate predictions.

REFERENCES

Aamer, A. M. (2018). Outsourcing in non-developed supplier markets: a lean thinking approach. International Journal of Production Research, 56(18), 6048–6065. https://doi.org/10.1080/00207543.2018.1465609

Aamer, A. M., & Sawhney, R. (2004). Review of suppliers selection from a production perspective. IEE Annual Conference and Exhibition 2004.

Affia, I., Yani, L. P. E., & Aamer, A. M. (2019). Factors affecting IoT adoption in food supply chain management. 9th International Conference on Operations and Supply Chain Management, 19–24.

Ahmad, T., & Chen, H. (2018). Utility companies strategy for short-term energy demand forecasting using machine learning-based models. Sustainable Cities and Society, 39(August 2017), 401–417. https://doi.org/10.1016/j.scs.2018.03.002

Ahmad, T., Chen, H., & Shair, J. (2018). Water source heat pump energy demand prognosticate using disparate data-mining based approaches. Energy, 152, 788–803.
Aksoy, A., Ozturk, N., & Sucky, E. (2012). A decision support system for demand forecasting in the clothing industry. *International Journal of Clothing Science and Technology*, 24(4), 221–236. https://doi.org/10.1108/IJCSST-07-2011-0044

Al-Musaylih, M. S., Deo, R. C., Adamowski, J. F., & Li, Y. (2018). Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Advanced Engineering Informatics*, 35(November 2017), 1–16. https://doi.org/10.1016/j.aei.2017.11.002

Alamaniotis, M.,ikononopoulos, A., & Tsoukalas, L. H. (2012). Evolutionary multiobjective optimization of kernel-based very-short-term load forecasting. *IEEE Transactions on Power Systems*, 27(3), 1477–1484. https://doi.org/10.1109/TPWRS.2012.2184308

Badri, A., Ameli, Z., & Birjandi, A. (2012). Application of Artificial Neural Networks and Fuzzy Logic Methods for Short Term Load Forecasting - ScienceDirect. *Energy Procedia*, 1883–1888.

Bekkari, N., & Zeddouri, A. (2019). Using artificial neural network for predicting and controlling the effluent chemical oxygen demand in wastewater treatment plant. *Management of Environmental Quality: An International Journal*, 30(3), 593–608. https://doi.org/10.1007/MEQ-04-2018-0084

Beyca, O. F., Ervural, B. C., Tatoglu, E., Ozuyar, P. G., & Zaim, S. (2019). Using machine learning tools for forecasting natural gas consumption in the province of Istanbul. *Energy Economics*, 80, 937–949. https://doi.org/10.1016/j.eneco.2019.03.006

BKPM. (2019). *Making Indonesia 4.0: Indonesia’s Strategy to Enter the 4th Generation of Industry Revolution* | Invest Indonesia. https://www.investindonesia.go.id/en/why-invest/indonesia-economic-update/making-indonesia-4-0-indonesias-strategy-to-enter-the-4th-generation-of-ind

Bolandnazar, E., Rohani, A., & Taki, M. (2019). Energy consumption forecasting in agriculture by artificial intelligence and mathematical models. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, 7036. https://doi.org/10.1080/15567036.2019.1604872

Bonnes, K. (2014). Predictive Analytics for Supply Chains: a Systematic Literature Review. *21st Twente Student Conference on IT Enschede*, 1–10.

Bousqaoui, H., Achchab, S., & Tikito, K. (2018). Machine learning applications in supply chains: An emphasis on neural network applications. *Proceedings of 2017 International Conference of Cloud Computing Technologies and Applications, CloudTech 2017*, 2018-Janua, 1–7. https://doi.org/10.1109/CloudTech.2017.8284722

Bower, JL, Christensen, C. (1996). Disruptive technologies: Catching the wave. *Journal of Product Innovation Management*, 13(1), 43–53.

Braun, M., Bernard, T., Piller, O., & Sedehizade, F. (2014). 24-hours demand forecasting based on SARIMA and support vector machines. *Procedia Engineering*, 89, 926–933. https://doi.org/10.1016/j.proeng.2014.11.526

Brentan, B. M., Luvizotto, E., Herrera, M., Izquierdo, J., & Perez-Garcia, R. (2017). Hybrid regression model for near real-time urban water demand forecasting. *Journal of Computational and Applied Mathematics*, 309, 532–541. https://doi.org/10.1016/j.cam.2016.02.009

Candelieri, A., Soldi, D., & Archetti, F. (2015). Short-term forecasting of hourly water consumption by using automatic metering readers data. *Procedia Engineering*, 119(1), 844–853. https://doi.org/10.1016/j.proeng.2015.08.948

Cao, J., Jiang, Z., & Wang, K. (2017). Customer demand prediction of service-oriented manufacturing using the least square support vector machine optimized by particle swarm optimization algorithm. *Engineering Optimization*, 49(7), 1197–1210. https://doi.org/10.1080/0305211X.2016.1245729

Carbonneau, R., Labramboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, 184(3), 1140–1154. https://doi.org/10.1016/j.ejor.2006.12.004

Chen, K. L., Yeh, C. C., & Lu, T. L. (2012). A hybrid demand forecasting model based on empirical mode decomposition and neural network in TPT-LCD industry. *Cybernetics and Systems*, 43(5), 426–441. https://doi.org/10.1080/01969722.2012.688691

Chen, S. C., Kuo, S. Y., Chang, K. W., & Wang, Y. T. (2012). Improving the forecasting accuracy of air passenger and air cargo demand: The application of back-propagation neural networks. *Transportation Planning and Technology*, 35(3), 373–392. https://doi.org/10.1080/03080965.2012.673272

Cheng, L., Chen, X., De Vos, J., Lai, X., & Witlox, F. (2019). Applying a random forest method approach to model travel mode choice behavior. *Travel Behaviour and Society*, 14(September 2018), 1–10. https://doi.org/10.1016/j.tbs.2018.09.002

Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications*, 83, 187–205. https://doi.org/10.1016/j.eswa.2017.04.030

Chopra, S., & Meindl, P. (2013). *Supply chain management: strategy, planning, and operation*. Pearson.

Chou, J. S., & Ngo, N. T. (2016). Time series analytics using sliding window metaheuristic optimization-based machine learning system for identifying building energy consumption patterns. *Applied Energy*, 177, 751–770. https://doi.org/10.1016/j.apenergy.2015.05.074

Chu, W. C., Zaim, S., Yeh, C. C., & Lu, T. L. (2012). Long term electricity demand forecasting model based on empirical mode decomposition. *Energy*, 37(3), 392. https://doi.org/10.1016/j.energy.2012.09.002

Claveria, O., Monte, E., & Torra, S. (2015). A new forecasting approach for the hospitality industry. *International Journal of Contemporary Hospitality Management*, 27(7), 1520–1538. https://doi.org/10.1108/IJCHM-06-2014-0286

Claveria, O., Monte, E., & Torra, S. (2016). Combination forecasts of tourism demand with machine learning models. *Applied Economics Letters*, 23(6), 428–431. https://doi.org/10.1080/13504851.2015.1078441

Çunkas, M., & Altun, A. A. (2010). Long term electricity demand forecasting in Turkey using artificial neural networks. *Energy Sources, Part B: Economics, Planning and Policy*, 5(3), 279–289. https://doi.org/10.1080/15567240802533542

Du, X. F., Leung, S. C. H., Zhang, J. L., & Lai, K. K. (2013). Demand forecasting of perishable farm products using support vector machine. *International Journal of Systems Science*, 44(3), 556–567. https://doi.org/10.1080/00207717.2011.617888

Elattar, E. E., Member, S., Goulernas, J. Y., Wu, Q. H., & Member, S. (2010). Weighted Support Vector Regression. *40(4), 438–447.

Ertugrul, Ö. F. (2016). Forecasting electricity load by a novel recurrent extreme learning machines approach. *International Journal of Electrical Power and Energy Systems*, 78, 429–435. https://doi.org/10.1016/j.ijepes.2015.12.006

Esseye, A. T., Lehtonen, M., Tukia, T., Uimonen, S., & John Millar, R. (2019). Machine learning based integrated feature selection approach for improved electricity demand forecasting.
forecasting in decentralized energy systems. *IEEE Access*, 7, 91463–91475. https://doi.org/10.1109/ACCESS.2019.2924685

Fang, L., Cheng, X., Wang, H., & Yang, L. (2018). Mobile demand forecasting via deep graph-sequence spatiotemporal modeling in cellular networks. *IEEE Internet of Things Journal*, 5(4), 3091–3101. https://doi.org/10.1109/JIOT.2018.2832071

Feki, M., Wamba, S. F., & Bouzidhala, I. (2016). Big Data Analytics-enabled Supply Chain Transformation: A Literature Review. *Hawaii International Conference on System Sciences*, 49, 1123–1132. https://doi.org/10.1109/HICSS.2016.142

Ferrara, M., Liberto, C., Nigro, M., Trojani, M., & Valenti, G. (2019). Multimodal choice model for e-mobility scenarios. *Transportation Research Procedia*, 37 (September 2018), 409–416. https://doi.org/10.1016/j.trpro.2018.12.210

Gao, X., & Lee, G. M. (2019). Moment-based rental prediction for bicycle-sharing transportation systems using a hybrid genetic algorithm and machine learning. *Computers in Industrial Engineering*, 128 (December 2018), 60–69. https://doi.org/10.1016/j.cie.2018.12.023

Golshani, N., Shabanpour, R., Mahmoudi, D., Derrible, S., & Mohammadian, A. (2018). Modeling travel mode and timing decisions: Comparison of artificial neural networks and copula-based joint model. *Travel Behaviour and Society*, 10 (October 2016), 21–32. https://doi.org/10.1016/j.tbs.2017.09.003

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. whole book. *Nature*, 521(7553), 800. https://doi.org/10.1038/nature14539

Hammandlu, M., & Chauhan, B. K. (2011). Load forecasting using hybrid models. *IEEE Transactions on Power Systems*, 26(1), 20–29. https://doi.org/10.1109/TPWRS.2010.2048585

Herrera, M., García-Díaz, J. C., Izquierdo, J., & Pérez-García, R. (2011). Municipal Water Demand Forecasting: Tools for Intervention Time Series. *Stochastic Analysis and Applications*, 29(6), 998–1007. https://doi.org/10.1080/07362994.2011.610161

Herrera, Manuel, Torgo, L., Izquierdo, J., & Pérez-García, R. (2010). Predictive models for forecasting hourly urban water demand. *Journal of Hydrology*, 387(1–2), 141–150. https://doi.org/10.1016/j.jhydrol.2010.04.005

Hong, W. C., Dong, Y., Chen, L. Y., & Wei, S. Y. (2011). SVR with hybrid chaotic genetic algorithms for tourism demand forecasting. *Applied Soft Computing Journal*, 11(2), 1881–1890. https://doi.org/10.1016/j.asoc.2010.06.003

Hribar, R., Potocnik, P., & Papa, G. (2019). A comparison of models for forecasting the residential natural gas demand of an urban area. *Energy*, 167, 511–522. https://doi.org/10.1016/j.energy.2018.10.175

Huang, J., Liang, Y., Bian, H., & Wang, X. (2019). Using Cluster Analysis and Least Square Support Vector Machine to Predicting Power Demand for the Next-Day. *IEEE Access*, 7, 82681–82692. https://doi.org/10.1109/ACCESS.2019.2922777

Huang, Y., Yuan, Y., Chen, H., Wang, J., Guo, Y., & Ahmad, T. (2019). A novel energy demand prediction strategy for residential buildings based on ensemble learning. *Energy Procedia*, 158, 3411–3416. https://doi.org/10.1016/j.egypro.2019.01.935

Huang, K. H., Yu, T. H. K., Moutinho, L., & Wang, Y. C. (2012). Forecasting tourism demand by fuzzy time series models. *International Journal of Culture, Tourism, and Hospitality Research*, 6(1), 377–388. https://doi.org/10.1080/17506181211265095

Huddiniah, E. R., & ER, M. (2019). Product Variety, Supply Chain Complexity and the Needs for Information Technology: A Framework Based on Literature Review. *Operations and Supply Chain Management: An International Journal*, 245–255. https://doi.org/10.31387/oscm0390247

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analyzes. *International Journal of Production Research*, 57(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Izadyar, N., Ong, H. C., Shamshirband, S., Ghadamian, H., & Tong, C. W. (2015). Intelligent forecasting of residential heating demand for the District Heating System based on the monthly overall natural gas consumption. *Energy and Buildings*, 104, 208–214. https://doi.org/10.1016/j.enbuild.2015.07.006

Jebbari, S., Inyain, S., & Goic, R. (2011). Forecasting of coal consumption using an artificial neural network and comparison with various forecasting techniques. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, 33(14), 1305–1316. https://doi.org/10.1080/15567030903397859

Jebie, S., Kumari, S., & Patil, Y. (2018). Role of big data in decision making. *Operations and Supply Chain Management, 11*(1), 36–44. https://doi.org/10.31387/oscm0300198

Jiang, S., Chin, K. S., & Tsui, K. L. (2018). A universal deep learning approach for modeling the flow of patients under different severities. *Computer Methods and Programs in Biomedicine*, 154, 191–203. https://doi.org/10.1016/j.cmpb.2017.11.003

Johannesen, N. J., Kolhe, M., & Goodwin, M. (2019). Relative evaluation of regression tools for urban area electrical energy demand forecasting. *Journal of Cleaner Production*, 218, 555–564. https://doi.org/10.1016/j.jclepro.2019.01.108

Joseph, A., Larrain, M., & Ottoo, R. (2013). Comparing the forecasts of money demand. *Procedia Computer Science*, 20, 478–483. https://doi.org/10.1016/j.procs.2013.09.306

Ke, J., Zheng, H., Yang, H., & Chen, X. (Michael). (2017). Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach. *Transportation Research Part C: Emerging Technologies*, 85(October), 591–608. https://doi.org/10.1016/j.trc.2017.10.016

Khosravi, A., & Nahavandi, S. (2014). Load forecasting using interval type-2 fuzzy logic systems: Optimal type reduction. *IEEE Transactions on Industrial Informatics*, 10(2), 1055–1063. https://doi.org/10.1109/TII.2013.2285650

Kialashahi, A., & Reisel, J. R. (2014). Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States. *Energy*, 76, 749–760. https://doi.org/10.1016/j.energy.2014.08.072

King, M. A., Abrahams, A. S., & Ragsdale, C. T. (2014). Ensemble methods for advanced skier days prediction. *Expert Systems with Applications*, 41(4), PART 1, 1176–1188. https://doi.org/10.1016/j.eswa.2013.08.002

Klute, B., Homb, A., Chen, W., & Stelpflug, A. (2019). Predicting Outpatient Appointment Demand Using Machine Learning and Traditional Methods. *Journal of Medical Systems*, 43(9), https://doi.org/10.1007/s10916-019-1418-y

Kofinas, D., Mellios, N., Papageorgiou, E., & Laspidou, C. (2014). Urban water demand forecasting for the island of skaiathos. *Procedia Engineering*, 89, 1023–1030. https://doi.org/10.1016/j.proeng.2014.11.220

Kone, E. R. S., & Karwan, M. H. (2011). Combining a new data classification technique and regression analysis to predict the Cost-To-Serve new customers. *Computers and Industrial Engineering*, 61(1), 184–197. https://doi.org/10.1016/j.cie.2011.03.009

Leipziger, D., Dodev, V., Leipziger, D., & Dodev, V. (2016). *Institute for International Economic Policy Working Paper*
Series Elliott School of International Affairs The George Washington University Disruptive Technologies and their Implications for Economic Policy: Some Preliminary Observations DISRUPTIVE TECHNOLOGIES AND THEIR IMPLICATIONS FOR ECONOMIC POLICY: SOME PRELIMINARY OBSERVATIONS.

Liu, Y., Zhang, Q., Fan, Z. P., You, T. H., & Wang, L. X. (2019). Maintenance spare parts demand forecasting for automobile 4s shop considering weather data. IEEE Transactions on Fuzzy Systems, 27(5), 943–955. https://doi.org/10.1109/TFUZZ.2018.2831637

Lou, C. W., & Dong, M. C. (2013). Intelligent self-developing and self-adaptive electric load forecaster based on type-2 fuzzy Bayesian Ying-Yang learning algorithm. Applied Artificial Intelligence, 27(9), 818–850. https://doi.org/10.1080/08839514.2013.835234

Maldonado, S., González, A., & Crone, S. (2019). Automatic time series analysis for electric load forecasting via support vector regression. Applied Soft Computing Journal, 83, 105616. https://doi.org/10.1016/j.asoc.2019.105616

Manyika, J., Chui, M., Bssis, P., Woetzel, J., Dobbs, R., Baghun, J., & Aharon, D. (2015). The Internet of Things: Mapping the Value beyond the Hype EXECUTIVE SUMMARY. McKinsey & Company, June, 1–18.

Mason, K., Duggan, J., & Howley, E. (2018). Forecasting energy demand, wind generation and carbon dioxide emissions in Ireland using evolutionary neural networks. Energy, 155, 705–720. https://doi.org/10.1016/j.energy.2018.04.1922

Mason, K., Duggan, M., Barrett, E., Duggan, J., & Howley, E. (2018). Predicting host CPU utilization in the cloud using evolutionary neural networks. Future Generation Computer Systems, 86(2018), 162–173. https://doi.org/10.1016/j.future.2018.03.040

Minal, S., Sehkar, C. R., & Madhu, E. (2019). Development of neuro-fuzzy-based multimodal mode choice model for commuter in Delhi. IET Intelligent Transport Systems, 13(2), 406–416. https://doi.org/10.1049/iet-its.2018.5112

Mouatadid, S., & Adamowski, J. (2017). Using extreme learning machines for short-term urban water demand forecasting. Urban Water Journal, 14(6), 630–638. https://doi.org/10.1080/1573062X.2012.1263133

Nagi, J., Yap, K. S., Nafi, F., Tiong, S. K., & Ahmed, S. K. (2011). A computational intelligence scheme for the prediction of the daily peak load. Applied Soft Computing Journal, 11(8), 4773–4788. https://doi.org/10.1016/j.asoc.2011.07.005

Norman, A., & Naslund, D. (2019). Supply chain incentive alignment: The gap between perceived importance and actual practice. Operations and Supply Chain Management, 12(3), 129–142. https://doi.org/10.31387/oscm0380237

Nose-Filho, K., LOTUFO, A. D. P., & Minussi, C. R. (2011). Short-term multinodal load forecasting using a modified general regression neural network. IEEE Transactions on Power Delivery, 26(4), 2862–2869. https://doi.org/10.1109/TPWRD.2011.2166566

Okoli, C., & Schabram, K. (2010). A Guide to Conducting a Systematic Literature Review of Information Systems Research. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1954824

Percy, S. D., Aldene, M., & Berry, A. (2018). Residential demand forecasting with solar-battery systems: A survey-less approach. IEEE Transactions on Sustainable Energy, 9(4), 1499–1507. https://doi.org/10.1109/TSTE.2018.2791982

Plakandaras, V., Papadimitriou, T., & Gogas, P. (2019). Forecasting transportation demand for the U.S. market. Transportation Research Part A: Policy and Practice, 126(June), 195–214. https://doi.org/10.1016/j.tra.2019.06.008

Puchalsky, W., Ribeiro, G. T., da Veiga, C. P., Freire, R. Z., & Santos Coelho, L. dos. (2018). Agribusiness time series forecasting using Wavelet neural networks and metaheuristic optimization: An analysis of the soybean sack price and perishable products demand. International Journal of Production Economics, 203(June), 174–189. https://doi.org/10.1016/j.ijpe.2018.06.010

Qiu, X., Ren, Y., Suganthan, P. N., & Amaratunga, G. A. J. (2017). Empirical Mode Decomposition based ensemble deep learning for load demand time series forecasting. Applied Soft Computing Journal, 54, 246–255. https://doi.org/10.1016/j.asoc.2017.01.015

Qiu, X., Zhang, L., Nagaratnam Suganthan, P., & Amaratunga, G. A. J. (2017). Oblique random forest ensemble via Least Square Estimation for time series forecasting. Information Sciences, 420, 249–262. https://doi.org/10.1016/j.ins.2017.08.060

Quan, H., Srinivasan, D., & Khosravi, A. (2014). Short-term load and wind power forecasting using neural network-based prediction intervals. IEEE Transactions on Neural Networks and Learning Systems, 25(2), 303–315. https://doi.org/10.1109/TNNLS.2013.2276053

Raguso, E. (2018). Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. International Journal of Information Management, 38(1), 187–195. https://doi.org/10.1016/j.ijinfomgt.2017.07.008

Rice, W. L., Park, S. Y., Pan, B., & Newman, P. (2019). Forecasting campground demand in US national parks. Annals of Tourism Research, 75(November), 424–438. https://doi.org/10.1016/j.annals.2019.01.013

Sahara, C. R., Damar, J., Paluluth, E., & Aamer, A. M. (2019). Exploring the key factor categories for the digital supply chain. 9th International Conference on Operations and Supply Chain Management, Vietnam, 1–11.

Sala-Cardoso, E., Delgado-Prieto, M., Ktpouropoulos, K., & Romeral, L. (2018). Activity-aware HVAC power demand forecasting. Energy and Buildings, 170, 15–24. https://doi.org/10.1016/j.enbuild.2018.03.087

Saloux, E., & Candanedo, J. A. (2018). Forecasting District Heating Demand using Machine Learning Algorithms. Energy Procedia, 149, 59–68. https://doi.org/10.1016/j.egypro.2018.08.169

Saxena, H., Aponte, O., & McConkey, K. T. (2019). A hybrid machine learning model for forecasting a billing period’s peak electric load days. International Journal of Forecasting, 35(4), 1288–1303. https://doi.org/10.1016/j.ijforecast.2019.03.025

Shi, J., Lee, W. J., Liu, Y., Yang, Y., & Wang, P. (2012). Forecasting power output of photovoltaic systems based on weather classification and support vector machines. IEEE Transactions on Industry Applications, 48(3), 1064–1069. https://doi.org/10.1109/TIA.2012.2190816

Spencer, B., & Al-Obeidat, F. (2016). Temperature Forecasts with Stable Accuracy in a Smart Home. Procedia Computer Science, 83(Seit), 726–733. https://doi.org/10.1016/j.procs.2016.04.160

Sun, S., Wei, Y., Tsui, K. L., & Wang, S. (2019). Forecasting tourist arrivals with machine learning and internet search index. Tourism Management, 70(June 2018), 1–10. https://doi.org/10.1016/j.tourman.2018.07.010

The World Bank. (2019). Indonesia | Data. https://data.worldbank.org/country/indonesia?view=chart

Tiwari, M. K., & Adamowski, J. F. (2017). An ensemble wavelet forecasting using Wavelet neural networks and metaheuristic optimization: An analysis of the soybean sack price and perishable products demand. International Journal of Production Economics, 203(June), 174–189. https://doi.org/10.1016/j.ijpe.2018.06.010

Varela, I. F. (2015). Big Data Analytics in Supply Chain Management: Trends And.

Vijai, P., & Bagavathi Sivakumar, P. (2018). Performance comparison of techniques for water demand forecasting. Procedia Computer Science, 143, 258–266.
Ammar Aamer, Professor of Industrial Engineering in the Faculty of Engineering and Technology at Sampoerna University Jakarta, Indonesia. He earned his B.S., M.S., and Ph.D. in Industrial Engineering from The University of Tennessee, USA. Dr. Aamer is an experienced professional with more than 22 years of academic and industrial experience. He provided consulting services to more than 30 international companies in the areas of Manufacturing Systems, Project Management, Supply Chain Management, Facilities Design and Layout, Process and Quality Improvement, Capacity Analysis, and Simulation Modelling. His research interests include Lean Manufacturing, Supply Chain Management, Simulation, Entrepreneurship, and Quality.

Luh Putu Eka Yani, Undergraduate student in the Department of Industrial Engineering Sampoerna University, Jakarta-Indonesia. Ms. Yani was the president of IEOM Student Chapter Sampoerna University. She also has been involved in many extracurricular activities and active research. Her research interests are supply chain management and entrepreneurship.

I Made Alan Priyatna, Full-stack developer in the Banking Industry. He obtained his undergraduate in Computer Science at Sampoerna University. His research interest includes image processing, machine learning, and automation.