Artificial Intelligence and Machine Learning in Supply Chain Optimization: A Review of Both Traditional and Machine Learning Techniques with Case Studies

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Abstract

In this paper, both traditional and new-born machine learning based techniques are reviewed, and some cases from previous papers are analyzed. Through this paper, it is found that machine learning based methodology, compared to the conventional ones, indeed provides better performance in increasing the accuracy of demand forecasting and reducing the cost of daily optimization and operation cost. This research is aimed to give a general review of techniques, and find out whether it is possible for machine learning based techniques can actually help companies to manage the supply chain with higher efficiency.

Key words: Supply chain optimization, machine learning, demand forecasting, business decision-making.

1 Introduction

As the supply chains become more and more sophisticated in the business world and the world changes much more rapidly than before, how to improve the techniques in supply chain optimization becomes a question that should be answered as soon as possible. Nowadays, here comes the era of boost of AI techniques. Especially after the artificial intelligence generated content (AIGC) models like chat generative pre-trained transformer (ChatGPT) occurred, Kashem et al. (2023) found that if we can apply it in business or even more precise fields like supply chain optimization,

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it can better satisfy increasing consumer expectations, unexpected demand fluctuation, and inventory costs [1]. There are several questions, however, that whether we can use AI techniques to accomplish supply chain optimization, whether its outcome makes a difference from the efficiency of traditional optimization, whether it has any drawbacks compared to the conventional one, and whether it is worth companies upgrading.

In the past, companies usually used traditional operations research as the main tool to optimize their supply chains. Here are several kinds of techniques that were used most in past decades: linear programming, integer programming, dynamic programming, simulation, and so on. Stadtler et al. (2015) claimed that companies wanted to achieve the lowest trucking costs, to decide where to locate warehouses, to know how to ensure the inventory is at the right place and right time, and so on [2]. Because the world moved relatively slowly and the change was manageable, these tools seemed to give out a great performance in the past decades.

However, facing the rapidly changing world, their drawbacks become clearer and clearer. Evolved customers' demands, sustainability issues, traffic exceptions, and natural disaster exceptions, Aqlan and Lam (2016) stated that all above mean that the conventional tools may not fit the world with more uncertainty and risks [3]. To be more competitive in business, companies have to figure out some new approaches to make some improvements. Simultaneously, numerous new techniques have been emerging such as AI, machine learning, and blockchain, and many firms have been applying these tools to their supply chain optimization. Generally speaking, they do improve the result in many situations. For instance, in a gradually more complicated supply network, it becomes difficult for linear programming to solve the issue because it involves multiple objectives and constraints that can only be tackled by tools like deep reinforcement learning, which can adapt to environments that are changing all the time and make optimal decisions. More specifically, Kashem et al. (2023) proved that blockchain technology can significantly reduce the need for verification, boosting supply chain management effectiveness with the goal of functional coordination, inter-firm collaboration, and eventually improving service quality [4]. Pournader et al. (2021) found there is no doubt that these new approaches also have shortcomings, such as the high price to buy or develop them, their need for a large amount of previous data to train, and so on [5]. As a result, whether it can bring more profits for every firm still needs to be evaluated.

No study to date has thoroughly investigated the comparison between AI-based supply chain optimization and the conventional one. Thus, the research goal is to review and compare the effect AI and machine learning implement on supply chain optimization, how they can distinguish these firms from their competitors, as well as to evaluate whether companies need to use AI techniques to optimize their complex supply chains. In section 2, we will review several traditional operations research techniques that are frequently used in supply chain optimization. Additionally, some machine learning based methodologies will be introduced in section 3. Then, there come the case studies in section 4 and the conclusion in section 5.

2 TRADITIONAL OPERATIONS RESEARCH TECHNIQUES

During previous decades, conventional operations research played a significant role in supply chain management and supply chain optimization. Among all approaches, there are several most typical and frequently applied techniques: linear programming, integer programming and dynamic programming.

2.1 Linear Programming (LP)

Stadtler et al. (2015) have illustrated that linear programming (LP) is one of the most well-known optimization techniques.

$$\mathbf{y_i} = \alpha + \beta \mathbf{x_i} + \varepsilon \, (\mathbf{i} = \mathbf{1}, \mathbf{2}, \ldots, \mathbf{n}) \text{ (Equation 1)}$$

This is the equation of simple linear regression. Y_i is the dependent variable, and x_i is the independent variable. In addition, α means intercept, and β is the slope of this model. ε_i is the error term, including some factors that have not been considered, some non-linear factors, etc. In conclusion, ε_i includes all factors affecting y_i except for x_i.

Linear programming is suitable for optimization problems involving multiple variables and constraints, and mature solving algorithms are available. Still, Stadtler et al. (2015) proved that linear programming is applicable in decision situations where variables can take any real values only restricted by linear equalities.There are many well-developed powerful solution algorithms that can solve linear programming models with thousands of variables and constraints within merely a few minutes on a normal computer. However, in the real world, situations change rapidly and there will always be some exceptions, which makes variables not linear anymore. Plus, handling multiple conflicting objectives in a linear programming model can be really complex. Supply chains in the real world often involve trade-offs between cost, service level, and other factors and this makes linear programming cannot do well. For instance, the company faces a situation in which producing a larger quantity of a product results in lower production costs per unit due to bulk discounts. However, this is a nonlinear relationship since the cost reduction is not proportional. Linear programming might not accurately capture this nonlinearity, potentially leading to suboptimal decisions. To overcome this limitation, nonlinear optimization methods are needed.

2.2 Integer Programming (IP)

$$\mathbf{y_i}= \alpha + \beta\mathbf{x_i}+\varepsilon\,(\mathbf{i = 1, 2, \ldots, n})\ (\mathbf{x_i isinteger})(\mathbf{Equation\ 2})$$

This is the standard equation of integer programming. Integer programming can be considered as special linear programming. As a result, the meanings of each variable are the same as the ones of linear programming above, except for the x_i here must be an integer. Integer programming extends linear programming by considering variables that must be integers, Stadtler et al. (2015) stated that it is applicable to problems requiring discrete decisions like resource allocation, bin packing, etc. The limit of integer programming is similar to the one of linear programming, and solving integer programming problems is more complex than linear programming, which may require longer calculating time.

2.3 Dynamic Programming (DP)

Essien (n.d.) illustrated that dynamic programming is a kind of problem-solving methodology that decomposes a sophisticated problem into several smaller sub-problems using recursive techniques to facilitate its simplification. It fits the situation with sequential decisions, considers optimal strategies across different decision stages, useful for long-term planning. Also, dynamic programming has its own drawbacks. The high computational complexity may lead to exponential computation times for large-scale problems. Plus, because the logic of dynamic programming is to break up problems into small pieces, it requires specific state transition equations and stage definitions for each problem.

One of the most common applications of dynamic programming in the business field is dynamic pricing. Den Den Boer (2015) stated that dynamic pricing refers to a methodology to determine or adjust prices according to market conditions, changing demands, and other factors in order to gain optimal revenue. In most conditions, dynamic pricing can be categorized into two kinds: dynamic pricing with dynamic demand, and dynamic pricing with inventory effects. Airplane ticket pricing is a well-known example. The demands of airlines are assumed that they are not a fixed function of price, but price derivatives. That is, the demand function is unknown. Over time, however, Bertsimas and Perakis (2006) claimed that it can be learned regarding price derivatives, price history, and numbers of sales using dynamic programming algorithms along with Bayesian structure and Markov decision process. This methodology can help set prices as state information is unknown, which can be significantly useful to maximize the revenue a firm makes.

3 METHODOLOGY OF MACHINE LEARNING (ML)

As the world changes faster and faster and the supply chains are of more complexity, the drawbacks of conventional operations research occur much more easily. Therefore, the firms figure out more methodologies based on artificial intelligence (especially machine learning) to solve the sophisticated problems they meet in daily operations. The following are some of the most prevalent machine learning techniques.

3.1 Reinforcement Learning (RL)

When using reinforcement learning as a supply chain optimization means, it will be provided with a series of actions, parameters, and values. Makkar, Devi, and Solanki (2020) stated that after the rules are set by humans, the reinforcement learning algorithm will try to test different options and possibilities, testing and evaluating each result to find out the best choice. It learns from past experiences and then adapts to the approach reacting to different situations to seek out the optimal possible result, especially in situations where a number of goals and constraints.It is often used to solve problems like route planning.

3.2 Neural Networks (NN)

As its name indicates, the way neural networks work resembles the nature of how a neuron works in human beings' brains.

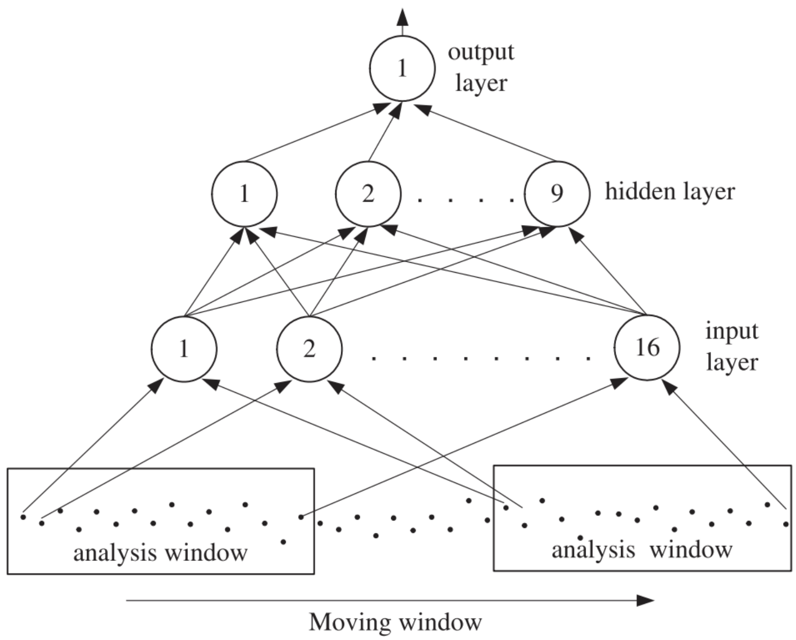

Figure 1: C.-S. Cheng and H.-P. Cheng (2011) : Structure of Neural Networks

Above is the structure of neural networks, and it explains how information goes in and out of neural networks. Makkar, Devi, and Solanki (2020) illustrated that in the networks, the neurons located in one layer passed signals through some links to another neuron in the next layer and they could only move in one direction. Moreover, Carbonneau, Laframboise, and Vahidov (2008) claimed that there were at least two layers named input and output layers in neural networks. The additional layers locate between the input and output layer, if there are some, are named hidden layers. These hidden layers are capable of increasing the computational power of the neural nets. Among all training algorithms, Rumelhart, Hinton, Williams, et al. (1985) stated that the most common one for the feed-forward nets is error back-propagation which is part of supervised learning. Given sufficient past data, patterns, and the relation of input and output, it begins learning and accomplishing future predictions. This predictive technique is commonly used in demand forecasting, warehouse management, manufacturing planning, dynamic pricing, and so on.

3.3 Clustering

Clustering is considered one of the most significant branches of unsupervised learning. Makkar, Devi, and Solanki (2020) claimed that unsupervised learning refers to the algorithm without the operator instructing to recognize patterns and grouping them according to some criteria. Xu and Tian (2015) proved that although the precise definition of clustering is still argumentative, clustering, to be specific, is able to segment the data with the principles below:data points in one cluster should of highly similarity, data points in different clusters should be dissimilar as much as possible and criteria of similarity and distance (dissimilarity) must be thoroughly clear and practical.

Landau and Ster (2010) stated that when applying clustering, it first selects the most representative features from the original data sets and then designs the algorithm according to the requirements and distinctions. Subsequently, it itself will evaluate the result and estimate whether the algorithm is valid or not. Finally, it gives out the clustering results which have passed the tests. In the real world, it is often used for customer segmentation, supplier assessment (to prevent a lot of potential risks), inventory classification (to get a more precise inventory management strategy), demand analysis (to enhance the accuracy of demand forecasting and inventory planning), etc.

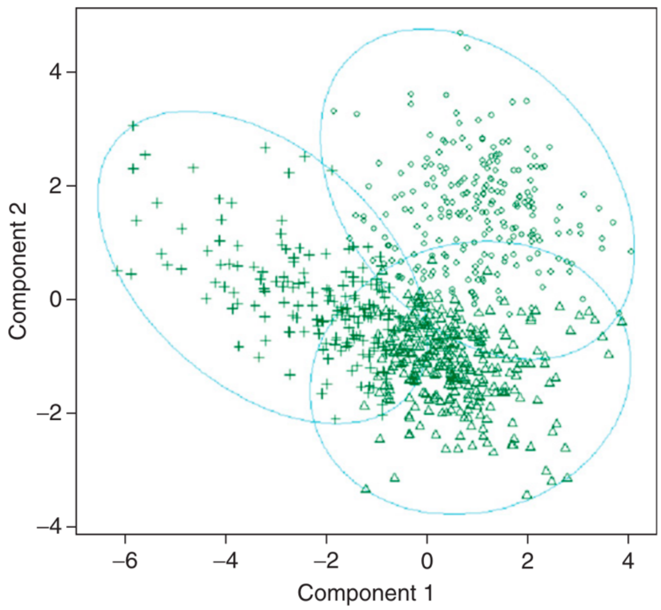

Figure 2: Xu and Tian (2015) : Scatter Plot of Data of Two Components

This figure clearly shows the first two principles mentioned above that data points in one cluster are highly similar and data points in different clusters are dissimilar as much as possible, which means clustering is able to segment data effectively.

4 CASE STUDIES

4.1 Demand Forecasting

Demand forecasting is a field in which machine learning applies most. Without an efficient demand forecasting procedure, there is a great chance that miscommunication between various company operations would reduce efficiency. On account of the capability illustrated by Ampazis (2015) of handling complex interdependencies between a large number of casual factors with non-linear relation patterns having an impact on the demand, Bohanec, Borštnar, and Robnik-Šikonja (2017) stated that forecasting based on machine learning empowered by predictive analytics has helped the firms to enhance customer management and gives out more accurate demand forecasts when they intended to expend new markets comparing with the traditional forecasting methods.Only a small number of characteristics, such as trends, seasonality, and price fluctuations, can be accommodated by traditional demand forecasting methods. Chase Jr et al. (2016) proved that contrarily, machine learning-based prediction methodologies can integrate large data and learning algorithms to concurrently examine and account for the vast majority of random components with non-linear relationships.

Here is a case. Feizabadi (2022) created a machine learning-based hybrid demand forecasting technique, and it was used and assessed in the context of functional products and steel producers. A steel manufacturing firm that engages in four distinct market areas, including production, retail, projects, and home appliances, provided the researcher with observational data. The impact of the new approach on the supply chain performance parameters of forecast accuracy, inventory turns, and cash conversion cycle was then examined by Feizabadi. Subsequently, he compared the performance of the new method with traditional time-series-based forecasting techniques, including Holt-Winter and Damped trend methods. In order to forecast the demand for steel products, the researcher also combined time series and exogenous (i.e., leading indicators) elements, notably those connected to environmental sustainability. Then he assessed the statistical significance of the variations in supply chain performance between conventional and ML-based demand forecasting techniques. Eventually, Feizabadi (2022) found that the forecast accuracy of the traditional techniques which is solely 84.1% can be boosted to 88.9% by using machine learning models.That was because complex causal and nonlinear linkages can be handled by machine learning techniques, which enhances supply chain performance and improves demand prediction. Furthermore, a hybrid approach that blends machine learning techniques with conventional time series methods has demonstrated benefits in terms of prediction accuracy. This 5% increase in forecast accuracy has the potential to significantly increase supply chain efficiency in capital-intensive sectors like the steel industry.

4.2 Decision-Making

Decision-making is another common field in which machine learning techniques are applied. Decision-making in supply chains like inventory management, route planning, risk management, etc. is severely challenged by high complexity, a combination of continuous and discrete processes, integrated and interdependent operations, and dynamic, and adaptability. Rolf et al. (2023)

proved that with the help of machine learning techniques like reinforcement learning, the firms are more prone to prevent disruptions and suboptimal performances caused by operational failures and information miscoordination compared with using conventional methodology.

To be more precise, machine learning is critical to reducing computing time and producing more precise decisions with fewer disturbances in large-scale optimization issues. Here is an example of a blood supply chain operational decision. Effective blood supply chain management is essential since blood is a scarce resource that must be procured from donors, is perishable, and cannot be kept in storage for an extended period after donation. In blood supply chains, the fundamental goal of inventory management is to optimally balance supply and demand to reduce wastage (also known as outdates) and shortages of blood units. Because of the erratic demand and perishable nature of blood units, there is a risk of overstocking or understocking, which raises the costs of shortage and loss. Hosseinifard and Abbasi (2018) found that transshipment is a successful strategy to increase the effectiveness of a blood supply chain. By such a policy, hospitals decide whether to order fresh blood from the central blood bank (CBB) as well as to transship some of their aging blood units to other hospitals in their network. The aforementioned choices must be made in a way that reduces the overall cost of the blood supply chain. Ordering, transshipment, holding, out-of-date, and shortfall costs make up the total cost. With so many constraints, Abbasi et al. (2020) still proved that the use of multilayer perceptron (MLP) models and, k-neural network model can help make optimal choices and reduce almost 20% of costs.The reason for this was that these neural network models could produce decisions for novel scenarios right away, provided that the supply chain network and distributions stayed the same, once they had been trained and taught from a small number of optimal solutions using a stochastic programming technique. As a result, the hospital could save costs due to the updated decision-making process and did not need to run the huge optimization models that provide optimal decisions.

5 CONCLUSION

This passage mainly reviews several types of commonly applied operations research techniques and machine learning methodology in supply chain optimization. In section 2, the basic principles of linear programming, integer programming, and dynamic programming and their applications are briefly introduced. Three machine learning techniques of reinforcement learning, neural networks, and clustering are explained in section 3. Also, except for its principles, the field in which they are usually applied is introduced.

Subsequently, there are two case studies about the application of machine learning techniques in demand forecasting and decision-making. In the demand forecasting case, a hybrid demand forecasting method grounded on machine learning was applied and evaluated in the context of a functional product and a steel manufacturer. By doing this research, the results showed that the forecast accuracy of the traditional techniques which was solely 84.1% could be boosted to 88.9% by using machine learning models, which clearly proved that machine learning based optimization methods were capable of providing a more accurate demand forecasting than traditional methods.

The second case of Abbasi et al. (2020) 's research on decision-making is a good example to illustrate that machine learning techniques provide a promising performance in the decision-making area and can effectively reduce the cost of techniques for the daily operation of a supply chain. The research results that the use of multilayer perceptron (MLP) models, and k-neural network model can help make optimal choices and reduce almost 20% of costs than traditional policies could be the proof of the assumption above.

These findings are highly consistent with the results of previous research. Because traditional forecasting techniques, such as econometric models, were incomplete for forecasting mineral commodity prices due to their static nature based on the belief that past events may be repeated, and machine learning has the ability to learn from past data to provide a predictive future pattern which is an excellent solution to forecasting complex situations, Cortez et al. (2018)'s research in mineral prices and demand forecasting claimed that machine learning is likely to have better performance for forecasting mineral prices compared to all other techniques.

However, this passage also has the limitation that the cases, applications, and data in it are still not so adequate to fully prove that traditional operation techniques must be worse than the machine learning based ones. In the future, more data and cases should be included in research to make an improvement. Future research direction can focus on providing more data to find out how can techniques combine to be better for firms to forecast customer demands, maximize revenues, reduce the daily optimization and operation cost, boost efficiency, and improve risk management of supply chain optimization.

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