Machine learning: Best way to sustain the supply chain in the era of industry 4.0

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ABSTRACT

With the rapidly growing importance in the industries on the adaptation of advanced technologies, the involvement of IT-enabled systems has increased in developing the pathway for the future industry. The learning's from these technologies becomes paramount for the present industries which gives a sense of belongingness and significance of the industry towards the market. The digital revolution world-wide affected the physical happenings of the events in the manufacturing industries such as the procurement, manufacturing/assembling & distribution of goods. This digital reformation is known as Industry 4.0 which generally means the advancement in the existing business models where all the business operations are interconnected with each other by digital mode (virtual representation based on operations). In this kind of environment, it is being necessary to map all the operations digitally in such a manner so that the physical flows of resources/goods will not suffer at any stage. Machine learning in the present scenario is one of the thrust areas for the researchers and the practitioners. The output in the machine learning process is having many dependencies on the input data such as the functions and characteristics imparted to the machine at the earlier stage. The present paper aptly reflects the thoughts and reflections of present-day industries and the opportunities to express feelings, thoughts, and contribute towards the future industries.

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1. Introduction

In industries, Supply Chain plays an extreme role in the success [26]. It's a complex integration of various business entities having a variety of technology and resource utilization [51]. Though the efficiency of a supply chain is dependent on various parameters, it seems to be difficult to design/develop a common platform where the integration of all the entities can be done centrally to enable industry the too quick respond to the market needs [7,21,56]. Generally, the SC helps industries in the following:

1. Establishing the strategic vision & mission of an organization

2. Understanding the customer on an individual basis (to create the pull from the customer end)
3. Help in increasing the competitiveness and flexibility by addressing all the issues
4. Providing the dynamicity to industry to find out the solution based on attributes such as quality, cost, time, risks, robustness, etc.
5. Increasing the real-time visibility of the industry environment to take prompt decisions
6. Optimizing the resource utilization
7. Providing opportunities to organizations on various fronts such as innovation, new product development, business strategies (B2N or B2C).
8. Developing an integrated model for scheduling problems based on location-routing in various situations such as cross-docking, direct shipment, etc.

D. Nagar, S. Raghav, A. Bhardwaj et al.

9. Motivating the employees and keeping them in the productive mode as per the workflow analysis.
10. Improving the performance on continuous basis and lead towards the perfection. [10,31,32,33,35,38,44,47,48,52,53, 59,70,86].

The literature on manufacturing industry performance reveals industrial growth dependency on the physical flow of the resources/goods throughout the supply chain [71]. In the small-scale industries (having less variety in goods i.e. product-mix), it is easier to manage the supply chain rather than in the large scale (offering variety in goods). Further, the prediction on the future forecast and the reliability of the forecast becomes an issue while handling the supply chain in uncertain environment conditions [72]. Now, it becomes essential to have better control over this value chain in the long term perspective [73].

The automation of the industrial entities is growing rapidly and increasing the competition rivalries where survival in long term becomes an issue for the industries [58]. For this, the industries are using software-enabled systems as the medium of communication to enable the organizations to withstand the latest trends [9]. Machine learning is the tool that helps in reducing/eliminating the negative influence of the data interpretation as this has no human involvement directly. It generally incorporates the large data set as the input in the system and responds quickly to the current requisitions/demands of the industries [74]. It helps in recognizing the situations and integrated these situations with the functions already in the system for preparing the models for analysis purposes. These models are further used for the decision-making process in the industries [5]. Besides, *ML* is used to estimate an appropriate forecast [6,63]. The present paper reveals the importance of Machine Learning in the industrial supply chain and briefs on benefits to the supply chain.

2. Literature review

The environment in the present scenario is dynamic and causes fierce competition among the manufacturing industries [17,66,77]. Also, in the earlier generations 1.0; 2.0, and 3.0, there were several issues with the industries like productivity, demand, and delivery, etc. The revolution in the IT sector started later in 1970, the movement worldwide in the industrial sector enforced the industry to think on the improvement aspect i.e. both the industry efficiency and efficacy perspective [11,41,67]. The terminology of Industry 4.0 is now studied by all the researchers and practitioners from the developing nation [54]. The other terms for Industry 4.0 are used such as smart manufacturing; intelligent manufacturing and factories of the future, etc. Industry 4.0 was firstly introduced in Germany in 2011, persistence to the customer needs and consistency in delivering the goods [87,4,50]. It enables and reinforces the industrial system to respond to the trend by using several tools/technologies [28,55].

The involvement of the cyber-physical system (CPS) was noticed as the industry moves towards the future [39,61,80]. Firstly, the concept of smart product was introduced which is in general the paradigm shift in the role of the workpiece from the passive to the active one. Sufficient data is created regarding the products like material requisition, operations in no's and timing at different workstations, etc., and stored for further use. As and when the demand is raised for the product by the customer, these details and requisitions come in the role for placing the order for resources and coordinates with the production facilities [18,57,62]. Later to this, the concept of smart machines has come into a role where the traditional machines are converted into smart ones by replacing or modifications based on the production hierarchy. The machines were interconnected like the plug-and-play

systems to respond to the production demand by eliminating the in process delays [30]. Another CPS system involvement in the industries was the Augmented Operator in which the operator skills are used to implement the automation which further makes an industry more flexible and adaptable [4]. In such kinds of industries, the operator has to play a variety of roles such as specification, monitoring, and validation of different production strategies [69]. Industry 4.0 has to target future aspects in industries related to innovation, flexibility, and complexity [88]. The six design principles in the Industry 4.0 are the: (a) Interoperability; (b) Virtualization; (c) Decentralization; (d) Real-time capability; (e) Service orientation and; and (f) Modularity [76]. It helps in enabling the flexibility aspect within the organization's operational activities which results in modifying the production system into mass customization and also helps in improving quality and productivity [87,84]. Most of the industries were working on a decentralized controlling system or in some cases the autonomous models were used for controlling the operations in the industries [80]. These kinds of models are now the biggest challenge for all kinds of industries because of the globalization of markets and competition [12,23]. To find out the solution, Industry 4.0 is the best option which aims to boost the communication among the industrial stake-holders and the resources to control centrally the discrete functions of an organization [36,45]. The resources in Industry 4.0 are converted into intelligent objects with the aid of technology so that they can sense and respond according to the desired situation for better business and societal outcomes [46,49]. The technologies that are playing the key roles in Industry 4.0 are the Internet of Thing, Cloud Computing (CC), Big Data Analytics (BDA), and Machine Learning and Artificial Intelligence (AI), etc. [14,15,37,43]. These advanced tools enable the industries to rethink resource utilization and establish a healthier relationship among the management and the value chain across the product lifecycle [29,83].

The supply chain of the industry, in general, is the path from which the resources flow from one position to another to meet the customer demand. In the supply chain the statistical data regarding the product/service is dependent on the various aspects like cost, region, gender, age, lifestyle, occupation, etc. [24,25]. Machine learning is one of the best tools in today's perspective as it is focused on the optimization of all the resource utilization throughout the value chain [16,82]. The algorithm designed in machine learning to predict/sense the inputs are consumer-centric and they allow machines to take prompt actions for the decisions regarding the situations [42,77]. The data input can be done by all the three modes of learnings i.e. with the help of a specially designed questionnaire or by constant monitoring (feedback based) etc. [22]. Machine learning generally provides reliable information as it precisely predicts the situation and helps in finding the best possible solution out of the alternative course of actions developed in the analysis [13,64,68]. In the logistic planning, ML serves as the statistical tool to conduct an in-depth analysis of critically important inputs by the market i.e. consumer feedback, market scenario, competitor analysis, etc. which further reduce the chances of pitfalls in potential consumers [75,81].

3. Research gap

Supply chain management generally discovers the various possibilities for the industry to optimum utilization of resources [10]. The product demand and supply is managed by the supply chain. Still, there are so many obstacles present within the supply chain that caused its performance throughout the value chain [3]. These obstacles are due to several reasons such as the length of the supply chain, uncertainty, effective communication, and the lack of

prediction on consumer behavior, etc. [19]. As far as the traditional supply chain management concern, the data input, and analysis were done manually that inhibits the effective handling of all the problems simultaneously [8,65]. The data collection becomes complex where no production and/or sales outlets are more. Also, it is observed in some cases that the analysis was not sufficient which leads to predict the negative influence of the integrity of industrial operations [78]. That's-why, it becomes difficult to objectifying the overall assessment of all the business entities of an organization especially in the case of dispersed (decentralized) production or the sales network [79]. The present paper will illustrate the necessity of machine learning in the supply chain and how it can be benefitted to the originations.

4. Methodology

In the present scenario, the industrial unit's performance is a major concern and the business owners are looking to find out the advanced tools that would help the industry to enhance the performance. In this regard, Industry 4.0 can be the better option which enables the industries to cope with the challenges within and outside the organizational boundaries regarding the efficiency and efficacy of the industries [85]. The Industry 4.0 tool, machine learning helps an industry to conduct all the activities automatically such as data gathering, structuring, and analyzing which are necessary for decision making under various situations. This can be done by giving directions to the machines through the pre-programmed certain algorithms. ML has the inbuilt features to recognize the new product demand and help in designing the same according to customer demands. In general, there are three types of machine learning i.e. a. supervised learning; b. unsupervised learning; and c. reinforced learnings as shown in Fig. 1 below [40].

In supervised learning, the labeled data i.e. data related to the functions/activities of any organization are entered into the machine and integrated with the various situations. Further, the data is labeled as per the user's understanding and based on labeled data machine will provide the information necessary for the decision making. In this case, the exact outcomes are provided to the user based on labeled data. In an unsupervised learning process, the data collected is divided into clusters which are further used for decision making [60]. In this case, the various courses of actions are introduced to the user for decision making. This learning process is quite complex to understand as this process never used the labeled data [40]. Reinforcement learning is also known as the reward based on the feedback given by the users. The negative feedback by the user regarding any object/situation is read by the machine as the relation between the data and function. These feedbacks actuate the internal system of the machine to recognize the object/situation and respond accordingly.

5. Research findings

Machine learning is a quite efficient solution while implementing it in the supply chain. It allows the industries to target the new goals of an optimum quality product with a low cost by the optimum utilization of resources. While implementing Machine learning in the supply chain, it becomes necessary to have perfection in developing the algorithms for sensing the data inputs and the analyzing tools. Further, in machine learning, the rigor's data sets are required to interconnect with each other. This interconnection should be done in such a manner that it helps in smooth the resource functionalities. The various roles of machine learning's in the supply chain are shown in Fig. 2 below:

5.1. Help in designing the smart workstations

The workstation generally refers to a place where the machines transform the raw material into semi/fully finished goods. Here smart workstations mean combining the machine characteristics with the other machines on the shop floor having a dependency
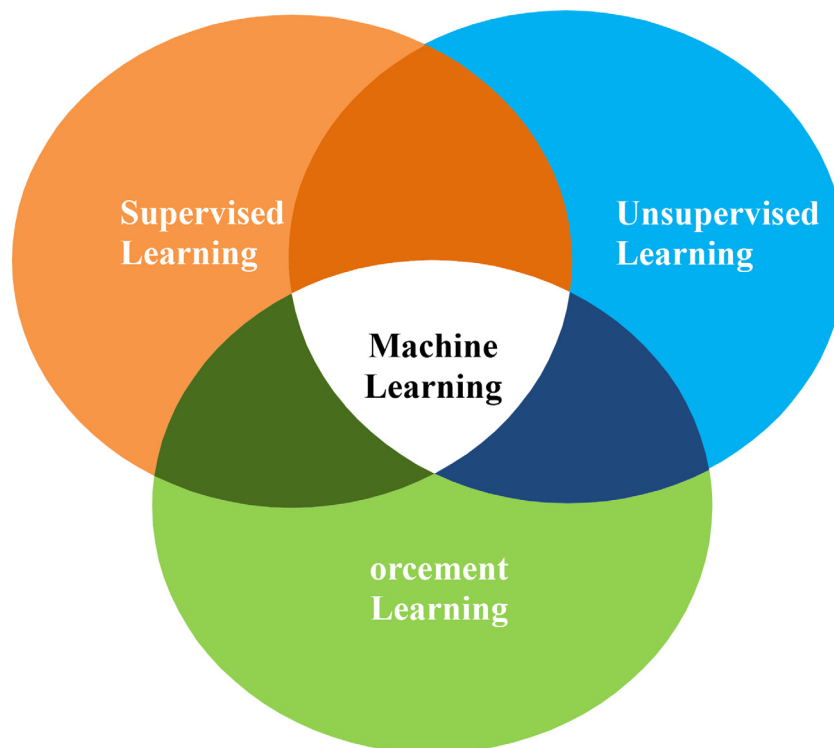

Fig. 1. Machine learning taxonomy.
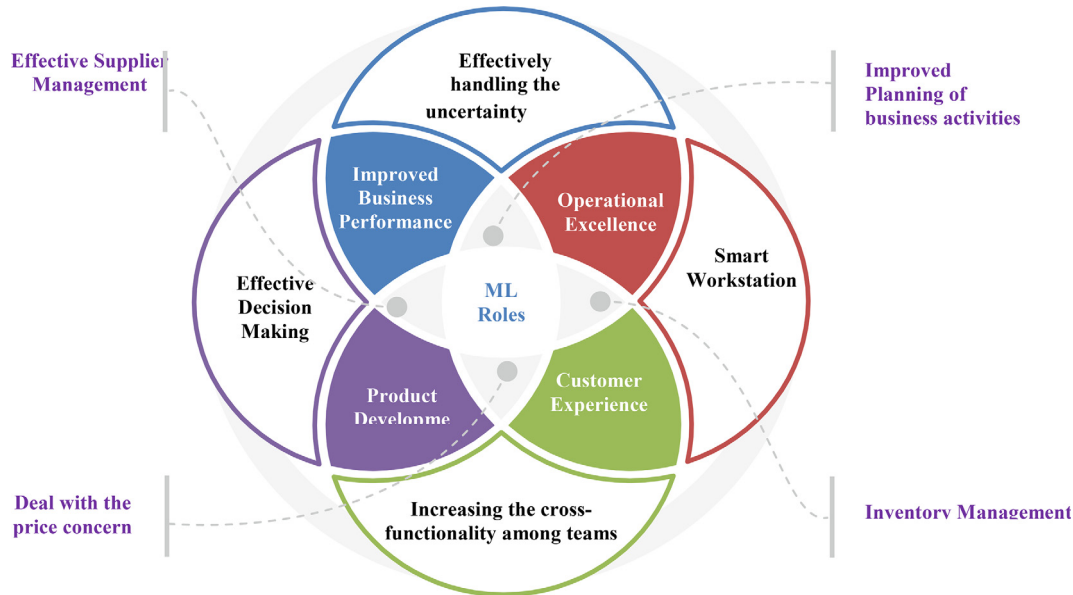
D. Nagar, S. Raghav, A. Bhardwaj et al.

Fig. 2. ML Roles in supply Chain.

on each other and providing the instructions to all the machines in such a manner so that the resource utilization can be optimized easily. Earlier this optimization work was done under the guidance of experienced personals and referee as continuous improvement. But now, sustainable activities are needed to be aligning to achieve the industry objectives effectively [27,34].

5.2. Help in providing the back support to the decision-making process in an organization

In the industries, the decision regarding operations such as procurement, production, distribution is having an impact on industry performance. Any mistake in analyzing the environment would cause a severe loss to the industries. Machine learning has the feature of analytical evaluation which helps in capacity building in an organization while taking the decisions in the industrial operations. Machine learning helps in providing decision support to the industry i.e. 'which kind of material is available in the market for the quality product and at what cost?'

5.3. Helps in handling the scalability

The implementation of SCM helps an organization to scale up the business because it can deal with a large no of verticals simultaneously. Still, the response rate is not quick enough in the traditional supply chain. Planning and delivering in the sudden influx of new orders requires enough time to understand which further cause delay in deliveries. These delays sometimes caused the delivery of the goods. Also, in fewer cases, it causes a negative impression on the brand, especially where the competition of the product in the niche are at of extreme level. This greatly concerns the heavy equipment industry where the shortest downtimes can lead to colossal financial losses. ML-based software development allows for minimizing these risks. For a sustainable supply chain, machine learning can play a tremendous role because it helps in dealing with uncertainty and keeps the industry ready for the upcoming challenges.

5.4. Helps in increasing the cross-functionality among teams

The literature on supply chain reveals that the better outcomes of SCM can be attained by implementing the IT-enabled system. But unfortunately, the industries are not integrating all the stakeholders of SCM with the IT-enabled systems. This makes things more challenging while accomplishing shared goals especially in dealing with the work done by a cross-functional team. Also, the decision regarding the product mix not only employs the extensive work capacity but also uses the quite complex tools/technologies to conduct repeated crash-tests for reducing the delays. The emergence of machine learning in the supply chain will provide a common platform for cross-functional teams to work with greater insights/intelligence across the teams. This will further lead to eliminating the unevenness in the supply chain and activities are done smoothly.

5.5. Helps in accelerating the operations

The earlier technologies successfully help in planning, organizing, and scheduling work right from procurement, production, stock, distribution, etc. In addition to that, the inclusion of machine learning will help in acceleration in the performance of all the operations within and outside the organizational boundaries through prediction and recognition of data related to a particular cause. The automated signals generated based on the prediction then helps in the decision making and improves the interconnectivity among the various operations. Forex. In the case of logistic planning and execution, machine learning accelerates the logistic operation by finding the optimum solution for the query like 'How fast the industry can deliver the goods to the consumers with the available alternatives in logistics?

5.6. Helps in the development of new products/services

In industrial psychology, it is not an easy task to develop and launch new products/services in the market. It requires the proper plan and schedule for development and launch. There is in-depth preliminary research on the market regarding targeted audiences and the product/service that they need? An industry utilizes its lot of resources to conduct this kind of researches to achieve the

objectives. Yet, this research can't direct an organization to a proper outcome in all the cases. Machine learning works with user interface and once the data-sets are introduced to the system, the system concludes all the consequences. Further helps in validating the consequence and maintaining transparency.

5.7. Helps in effective supplier management

In the supply chain, supplier collaboration is one of the biggest challenges to handle. Also, the supplier quality management i.e. the product/services delivered by the suppliers are of acceptable quality or not is also another aspect. The machine learning implementation in the supply chain will lead to manage the supplier quality as it provides a powerful pattern recognition technique. These patterns offer a quick response to the supplier's quality level with high accuracy and also create the logs for all activities that happened between supplier and manufacturer. Further, machine learning precisely examines the products/materials supplied to the industry and confirms the adherence to meeting the minimum criteria.

5.8. Helps in improving the demand and production planning

The concept of the supply chain was originated to bridge the gap between supply and demand in the earlier 19th century. But now it becomes a powerful tool to increase the industry effectiveness by integrating all the stakeholders and optimizing their work. Still, while working on demand and production planning in the traditional supply chain is not the effective one and that's-why the concept of a sustainable supply chain comes into existence. Also, the lack of objectiveness in the human experts bound the researches on the data analysis on demand prediction in the traditional supply chain. The literature on SCM reveals that the analysis in the traditional supply chain was influenced by the biases of the decision-maker and the unjustified market speculations. For that purpose, the inclusion of machine learning is the best option. Machine learning featuring better production planning because it helps in identifying the consumer requisitions and their pattern to purchase in different scenarios. The précised analytical information is provided by the algorithms employed in the ML which helps in neutralizing and rendering the data for verification purposes. This will help an organization to stand steady among other competitors.

5.9. Helps in handling the inventory-related issues (creating pull system)

In the industries, there are several issues related to the inventory like stocking cost, the product shelf-life, space requisition, unnecessary material handling, etc. bound them to take appropriate/prompt decisions which some time goes against the industry [20]. Especially in the case of food products, the shelf-life is the biggest challenge because the food products if not sold in a certain period get spoiled and lost to the industry. Further, in a few cases, the insufficiencies of the material cause the production as well as in few cases to increase the no of dispatches. Machine learning enables the industry to eliminate the buffers of inventory by keeping track of the several attributes simultaneously within and outside the organization. This is generally known as the pull system in which the material is procured and directly enters production based on consumer demand. An optimum stock level further helps in driving secure future events. With the aid of IoT systems, ML helps in handling the all-around inventory issues i.e. 'How many goods are in stock at the retail store/warehouses to prompt the decision regarding production and delivery of goods?'

5.10. Helps in deciding the price of a good/service

Determining pricing is the crucial task and considers both (the internal and external) determinants contributing to manufacturing/generating the product/service. It is important while determining the price, to position all these determinants in such a manner that they should help in pricing which generally meets the customer expectation and profitable to the manufacturer. Mostly, it is observed that the products fail to target the customers just because of inappropriate pricing determination at the manufacturer/service provider's end [34]. ML helps an organization to decide the price based on real-time data and if required, help in deciding the price with additional offers/promotions to increase the market share.

5.11. Safeguard in harnessing the uncertainty

In the industries, the presence of decentralization in the organizational structure limits the scope of SCM while discussing sustainable or consistent performance. ML is having the real-time capability inputs about the resources and activity in respect of quantity and time. Based on this, ML collects the data; does analysis, and provides the necessary inputs to decide to deal with the dealt situations. ML allows industries to reduce human intervention and at the same time, boost the preciseness and effectiveness of work processes.

5.12. Helps in improving consumer satisfaction

In the supply chain, the customer experience is kept at the utmost because it is directly related to the demand for products/services. The higher the consumer experience helps in increasing demand and vice-versa. ML will help the consumers to find real-time data by enabling the features within the system. It enables a quick response to the consumer query/feedback that further leads to greater consumer satisfaction.

6. Result & conclusion

As of today, the industries need to strengthen the supply chain for reasons such as market share, new consumers, creating the brand, and many more. The present paper reveals the opportunities for the industries to capitalize on their resources. For this purpose, machine learning is one of the best options, if implemented, it can benefit the industries in both tangible and intangible manners. The paper also gives an insight into the areas where industries mostly lose their efficient resources just because of decentralization in the supply chain. Machine learning provides the common (centralize) platform to pursue common goals considering the functional capabilities of all the stake-holders. As far as the positive roles of machine learning in the supply chain there are few negative aspects also such as requisition of huge investment initially; skill-set for establishing relationships among input data and organization functions (integration work) and the background history collection for all the operations and activities in an organization etc. In the future, the application of the SCM model in the FMCG products manufacturing industry.

CRediT authorship contribution statement

Devashish Nagar: Methodology, Writing - original draft. **Sudhanshu Raghav:** Methodology, Writing - original draft. **Aman Bhardwaj:** Resources, Writing - review & editing. **Rajender Kumar:** Conceptualization, Supervision. **Punj Lata Singh:** Investi-

gation, Project administration. **Rahul Sindhwani:** Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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