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Distributed Manufacturing for Digital Supply Chain: a brief review and future challenges

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Abstract. The rising demand for customization and increasing convergence of the physical and digital worlds have led manufacturing companies to seek solutions to maintain competitiveness in the global business landscape. Distributed manufacturing (DM) enables small volume customized production in geographically dispersed locations and drives the supply chain (SC) to become more agile, flexible, and sustainable. This review paper aims to present future research opportunities and challenges for the facilitation of DM for digital supply chain (DSC) by emerging digital technologies and artificial intelligence (AI). After a review of DM, we identify three distinct types of DM platforms that may facilitate DSC based on transaction mechanisms. These are then explored from a technological perspective, in terms of enabling technologies and data analysis methods that support DM for DSC. We conclude by highlighting the need for empirical studies to investigate the motivations for DM platform adoption and identify a key challenge to their adoption, that is the lack of privacy-preserving AI algorithms in facilitating DM.

Keywords: Distributed Manufacturing, Supply Chain, Digitalization, Artificial Intelligence, Machine Learning, Agent-based System.

1 Introduction

The rising demand for customization, has become a critical factor for companies to gain competitive advantage over their competitors [1]. Studies found that greater customization drives a 5–15 percent increase in revenue and a 10–30 percent increase in marketing-spend efficiency [2]. On the other hand, as part of globalization trends, many companies shifted their production plants to countries where labor and/or raw material costs are low, with the aim of mass producing standardized goods at a single location and achieving economies of scale [3]. The rising demand for customization poses a contrast to mass production, requiring companies to seek solutions in achieving rapid supply

chain reconfigurability such that parts to produce alternative product configurations can be sourced reliably, at short notice.

In tandem, the need for more resilient supply chains has been increasing. Most recently, with Covid-19 lockdowns in place, the imperative restrictions caused production shutdowns and/or logistics disruptions. This brought another tremendous pressure to manufacturing companies worldwide. A survey shows 47% of companies cited delays at end customers are the most considerable risk [4]. In addition, more than 80% of organizations are currently experiencing difficulties in recovering from SC disruptions in the short term [4]. Many organizations have encountered challenges in adjusting their production plans to ensure timely delivery of goods when faced with supplier delays. Inappropriate decision-making due poor information exchange in the supply chain led organizations to produce unnecessary waste in production, logistics, and human resources [5].

The above two imperatives yield an urgent need to devise an effective SC strategy for overcoming these challenges. DM has been proposed to be one of the approaches for manufacturing industries to overcome these challenges [6]. DM itself involves bringing together a collaborative, rapidly reconfigurable network of producers to allow resilient mass customization. However, the concept is not widely adopted partly due to the difficulty of its implementation. Rapid reconfiguration necessitates rapid information exchange and thus digital tools to help. There is a lack of understanding of state-of-art technology applied to DM when digitalizing the production and SC. It is therefore necessary to carry out research on how to enable DM from a digital infrastructure perspective and how the current methods and tools can be integrated into DM.

The main objectives of this paper are thus to (1) investigate the state-of-the-art applications and technologies applied to DM for Digital supply chain (DSC), (2) identify digital DM implementation challenges and future research opportunities from the perspective of DSC. The rest of this paper is organized as follows: in section 2, DM concept and features are described, and types of DM platforms supporting DSC are presented, in section 3, current technology enablers are reviewed, followed by derived challenges and future perspectives discussed in section 4, and conclusion in section 5.

2 DM for digital SC

2.1 Review methodology

This review is conducted based on two major databases (Web of Science and Scopus) variety of internet websites such as Google Scholar, Research Gate, etc. for searching relevant publications. We focus on data collecting, exchanging, and analyzing tools and methods in DM for DSC. The key search terms “Distributed manufacturing” and “Digital supply chain” incorporated with “CPS”, “IoT”, “Artificial Intelligence”, and “Data analytics” are selected from publications of summarized emerging digital technology enablers from production [7] and DSC [8] through April 2022. The outcome of this review is a summary of digital technology enablers in DM and their impact on production and DSC performance.

2.2 DM concept and features

DM is an evolving concept [9], although it has been around for more than two decades. Many studies [10-13] have attempted to define DM which was ultimately converged on 5 key characteristics: digitalization, personalization, localization, new manufacturing technologies, and multi-user participation [13]. In this study, DM is defined as “*A collaborative network of distributed manufacturing facilities that utilize new emerging advanced technologies to meet personalized and customized demand in an agile, flexible, sustainable, and demand-driven manner*” where:

“*Collaborative*” [14] implies the intra- and inter-organization coordination and collaboration within the network which all stakeholders are involved,

“*Distributed*” [13] refers to different locations of production sites which are either independent or belongs to a single enterprise. It also implies a non-hierarchical relationship between the facilities within the network and a need for flexible, rapid supply chain coordination,

“*Agile, flexible, sustainable, and demand-driven*” [13] emphasizes the objective of DM, which aims to tackle the current manufacturing challenges.

To adapt DM, manufacturers need to both rethink their manufacturing strategy and readjust their supply chain configuration. Manufacturing companies need to find ways to optimize procurement by extensive cooperation with a more dynamic supply network. Thus, a DSC network with reliable business relationships and shared economic interests will significantly enhance the competitiveness of enterprises.

2.3 DM platforms

One of the key DM implementation strategies has been to outsource parts from suppliers who have available manufacturing resources at the time. Manufacturing companies decouple the primary manufacturing processes and outsource to the available suppliers when demand is increased [15] with a short-term partnership. However, it is challenging to adopt an effective DM strategy due to the long evaluation and audit processes involved in a traditional SC. As demand drives the production of customized goods, it is time sensitive and purchasing from established suppliers is not always feasible. Consequently, DM deployment may require a third-party facilitator to act as a bridge that connects organizations.

The third-party facilitator integrates information on distributed manufacturing resources and their capacity and helps allocate these resources to cater to demand. It enables cooperation, sharing, and optimization of manufacturing resources between organizations to improve their responsiveness and competitiveness in the market. Recent studies presented several platforms to coordinate manufacturing resource sharing [16-18]. The ultimate objective of the proposed platforms is aligned with the purpose of DM and share the same characteristics with DM. Therefore, this research classifies them all as DM platforms.

A DM platform consists of three main actors: supplier, client, and platform provider. The distinctions between each platform are based on the transaction mechanism and the authority exerted over distribution. Transaction mechanism refers to the mechanism

with which the platform operates the process of making a deal, and authority exerted over distribution refer to the points of decision-making. One platform can have the same authority distribution with different transaction mechanisms, but not vice versa. Three types of DM platforms are identified based on transaction mechanisms as (1) **Task Assignment** [19]: The service provider dominates the transactions and facilitates quoting, matchmaking, and task assigning. Clients cannot communicate with suppliers directly. (2) **Yellow page** [20]: Supplier publishes capabilities and contact info on the server. The service provider does not involve in any transaction activities. Clients are free to communicate with suppliers. (3) **Auction-based** [14]: Client submits order to service provider, it will be either published in the system or broadcasted to the suppliers. All registered suppliers can access order information through the platform and bid. The client makes decision based on the offer(s).

DM platform benefits both ends from accessing richer manufacturing resources and leveraging idle production capacities. Different types of platforms support manufacturing companies to create values in various ways. Developing a successful DM platform involves an in-depth grasp of the business's challenges and demands. A critical factor for DM platform development involves sophisticated manufacturing and information technologies to facilitate DSC which requires better visibility of operation.

3 DM digital technology enablers for SC

3.1 Agent-Based System

As a collaborative network of geographically dispersed facilities, efficient and effective collaboration between organizations is crucial to the success of DM for SC. The primary approach utilizes an agent-based system (ABS) to design cooperation mechanisms between agents to enable automated collaboration. The implementation of ABS in DM is considered from different organizational levels. Li [21] developed two-level ABS (Sub-EMAS and EA-MAS) which aim to schedule manufacturing resource sharing through both intra- and inter-organizational views.

Most ABS research in DM has focused on resource scheduling in manufacturing. There are three types of DM scheduling based on the manufacturing resource attributions [21]. (1) Manufacturing resources are owned by the same organization and located in different sites [22]. (2) Manufacturing resources belong to multiple organizations and located in different sites [23]. (3) Manufacturing resources deliver to organizations across the supply chain [24]. Due to the complex and dynamic nature of DM environment, manual decision-making processes on resource sharing is not cost-effective. Thus, one of the main objectives of ABS is to provide efficient and accurate decision-making through automation.

Several negotiation methods were proposed to solve scheduling problems in a centralized approach via a third-party agent. However, risks are exposing sensitive information to the opponents and the third-party during the negotiation process. Also, the third-party agent can be a bottleneck that will potentially impact performance. An agent-based framework was proposed to improve the efficiency of the decision-making process during multiple shipbuilding project planning using an iterative combination

auction method [25]. Szaller [14] designed an auction-based DM resource sharing platform, agents place biddings to compete for production tasks in a federated architecture. Since each agent maintains production data only at local, they may use false information to bid on auctions, leading to production issues. However, local evaluation by distributed agents and lack of information exchange results in poor scheduling quality. Hsu [26] proposed an agent-based fuzzy constraint-directed negotiation (AFCN) mechanism to solve related privacy issues in heterogeneous production information sharing. Although this approach can effectively reduce the risk of information leakage from an agent, but it assumes that each agent has access to local information. Companies are less likely to allow third party agents access to their production information due to information privacy concerns. Several studies [14, 25] stated the same concerns and suggested that collaboration among agents is inefficient due to information privatization.

3.2 Data Acquisition and Transmission

Maintaining stable, efficient manufacturing resource allocation processes require sufficient data to support coordination and control between different units and facilities. The development of new Information and Communication Technologies (ICT) has empowered information flow in DM. ICT enables DM facilities integration with ERP, MES, and CRM, extracting insights from raw data and data embedded in various equipment, devices, and product objects via IoT. IoT utilizes various types of sensors to transmit and gain real-time visibility of progress, stock level, quality, energy, and logistics through wireless routers or cloud servers. For example, several IoT-based frameworks [27, 28] were proposed to monitor and analyze energy consumption for machine workshops in the DM facilities to improve energy efficiency, energy consumption and reduce cost. To achieve sustainability, Turner [29] embedded RFID tags on construction assets and materials incorporating with Building Information Model to build modular buildings in a DM scenario. IoT combines with Cyber-Physical systems (CPS) in production floor shops to enhance the data transmission and control between production units. Krishnamurthy [30] proposed an IoT-based CPS framework leveraging sensors and cameras to incorporate Virtual Reality (VR), supporting users and engineers to virtually interact with the PCB assembly process from the DM environment. Yang [31] developed a CPS-based platform to monitor automotive production sites across the globe. This platform integrated Digital Twin (DT), which creates information models to synchronize and visualize the real-time status of the part supplier, sub-assembly supplier, and OEM. The current studies on data collection and transmission mainly focus on sole organization. Capturing data from multiple parties across SC to achieve DM is still challenging.

3.3 Machine Learning

Distributed production facilities produce and collect datasets via various information collection and transmission technologies. Diverse data sources in DM include supplier, manufacturing, product, sales, customers, and financial organizations [32].

The key processes to use datasets in DM include data preprocessing [33] and data analytics. Data preprocessing methods, including data integration, reduction, and transformation, aim to eliminate inconsistency and prepare necessary data without noise for learning models. For example, text mining is applied to cleaning and extracting data from various sources such as machines, operations, materials, and manufacturing processes to prevent unnecessary bias.

Data analytics techniques can then be applied to draw managerial insights after data preparation. Previous works used the traditional mathematical methods such as mathematical programming model [34], and optimization [35] focusing on distributed shopfloors scheduling to improve efficiency and manufacturing resource utilization. Due to the high volume of real-time stream data and dynamic environments in DM, methods using deterministic models are not effective enough and researchers increasingly move to Machine Learning methods. Ramakurthi [34] presented a case study of gear industry and proposed a hybrid method using classification and mixed integer non-linear programming (MINLP) models to select suitable suppliers with a multi-objective optimization of lead time, reliability, energy consumption, and service utilization rate. Agostino [17] applied regression models including AutoRegressive Integrated Moving Average (ARIMA) and Neural Network Auto Regressive (NNAR) to forecast production time based on historical production data and used objective functions to optimize production order allocation across multiple production facilities. Bhsekar [36] applied a similar mixed approach with a support vector machine (SVM) model to approximate feasible production regions and design an optimal DM SC network. Classification and regression are two branches of supervised learning in Machine learning (ML). ML models can effectively aid the decision-making process in identifying trends and patterns from large sets of unstructured data. Although, the current research using ML approach in DM is limited, a few studies have applied ML models to predict order lead times [37], perform preventive maintenance [38], and predict disruptions with new task arrivals [39], all of which can potentially support DM in SC. However, there is a lack of study to address information silos issues when utilizing data across organizations as well as data privacy and security concerns when integrating heterogeneous DM data.

4 Challenges and Future Perspective

The advantages of DM platforms lie in facilitating information sharing and allocation of manufacturing resources dynamically. Manufacturing companies have adopted three types of DM platforms. But attracting more participation remains a question since larger user pools make the DM platform more effective. There is a need to conduct empirical studies to develop a systematic understanding of industrial perceptions when adopting DM platforms from aspects of (1) Motivation, precisely the reason to adopt DM platforms from perspectives as the client, supplier, or platform provider. (2) Capability, determine the status of DM technology enablers' adoptions, especially for SMEs, since facilitating SC activities in DM highly demands information technology infrastructure. (3) Challenges, identifying technological and managerial barriers for DM implementation for DSC.

The study of ABS in DM has been extensively conducted, but there is still a rare number of applications that have been applied in practice. There is a lack of trust in AI in executing important task including placing order and production scheduling without human interaction [40]. It challenges the reliability of data source and the precision of analysis. The current information acquisition approaches do not specifically address production and DSC data collection method between different organizations. For example, it should clarify whether data needs to be derived from both MES and ERP systems as well as the categorizations. There is no standard of identifying the core data group and this can lead to inefficient and inaccurate analysis due to complexity of manufacturing data. Significantly, there is a need to identify the essential data categories and establish a standard which allow precise, efficient, and low-cost data acquisition process via existing information technologies.

On the other hand, data security is a vital concern when transmitting data between organizations. DM platform requires sufficient data information from various sources among stakeholders. Although there are established standards, protocols, and technologies such as Blockchain technology (BCT) [41] have been proposed to guard data security for DSC, these approaches were not utilized in a DM environment. Moreover, transparency and traceability enabled by BCT may not be sufficient for DM since companies are unwilling to transmit sensitive information including production and purchase order data, making it challenging to conduct data analytics in DM. Also, most ABS studies assumed data accessibility when acting as a third-party facilitator. Data analytics is a crucial requirement for DM platform to facilitate automated matches between suppliers and buyers. Thus, an important future research direction to advance the use of DM platforms includes developing privacy-preserving algorithms such as federated learning which allow DM stakeholders to keep their sensitive data while allowing analytics to be performed.

5 Conclusion

This research focused on DM for DSC and a review is carried out to (1) examine the existing DM implementation approaches and three major types of DM platforms are classified, (2) investigate the state-of-art DM technology enablers including data collection, exchange, and analysis technologies, and (3) provide challenges and future research opportunities which include challenges of adopting DM platform from the industrial perspective, data acquisition methods, and data privacy concerns for analysis in real life industrial practice.

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