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Conference Paper · March 2023

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Big Data and Simulation In Lean Manufacturing From The Industry 4.0 Perspective

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Among industry players, the success rate with the adoption of Lean Manufacturing (LM) has been growing significantly year-over-year, by leveraging the Industrial Revolution of 4.0. The boom in Industry 4.0 has resulted in exponential data growth in all fields. This has been possible due to the big data exchange system in real-time, which enables engineers to gain complete control of the system to deal with any forthcoming situation, including data collection and machine control. This scenario also results in competition encouraging the manufacturing industry to grow, thereby increasing the demand pool to cater to the market requirements. However, in real industry, engineers face issue with time, with regards to shortening the notification time when a mistake occurs, which is critical for decision making. Thus, in this review, researchers have tried to find a solution. Simulation can be employed to exploit a new concept of the solution to address complex data-based problem, and concentrate on the decision support system. This research tries to discern and diagnose the gap between the merging of both simulation as well as implementation of LM.

Keywords: Lean Manufacturing, IR4.0, Big Data, Simulation, Decision Support System

1. Introduction

The lean philosophy can be called as a production methodology that can be implemented to maximise value and reduce waste in the entire manufacturing process [1]. Since then, it has been recognised and adopted globally and has been the subject of ongoing discussion for more than 10 years [2]. The evolution in knowledge system has opened doors to limitless possibility regarding the integration of IR4.0 technology along with the lean philosophy and has garnered a lot of interest amongst researchers [3]. Due to this, thorough literature evaluations have been deducing how LM can be effectively integrated with Industry 4.0 to increase productivity. IR4.0 has been regarded as an industrial revolution that has helped redefine the way humans associate with one another as well as operate equipment by employing Technology Enablers, as presented in Figure 1 below, which is a huge shift for the humanity altogether. This revolution focuses on transformative actions like the Internet of Things (IoT), enabling a smart environment integrating human intelligence with the latest technical advancements [4].

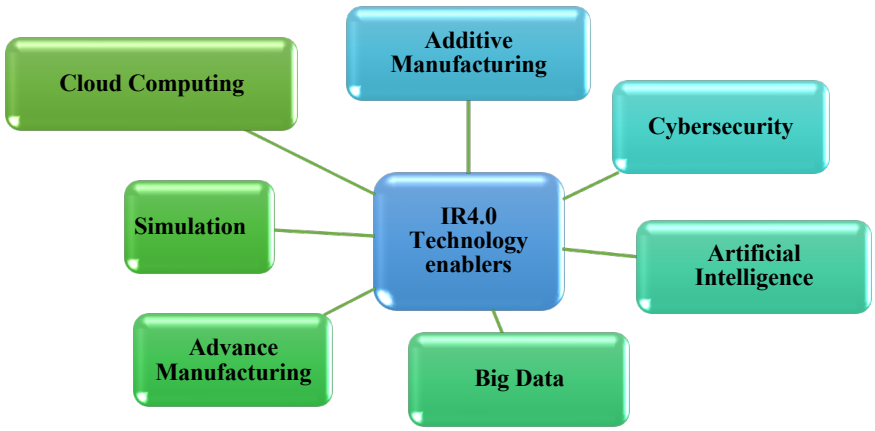

Figure 1: IR 4.0 Technology Enablers [4]

It looks like the rapid development of Industry 4.0 has resulted in explosive data expansion in every discipline, particularly in implementation of LM [5]. In certain ways, this could result in occurrence of sophisticated data processing throughout the entire processing line. With regards to lean manufacturing, which emphasises on continuous improvement, high consumer demand results in increase in variation diversity as well as intensity [6]. Nonetheless,

producers need to answer to consumers' requests promptly as data processing is complex [7].

This has given rise to a new question: what is the role of the Decision Support System in deploying LM in the IR4.0 era? With regards to this topic, and the fact that data is becoming more abundant each day, the researchers evaluated the present decision support system framework concerning LM implementation in this research work.

2. Research approach

2.1 Diversity Study on Industry 4.0

This study follows a systematic literature review philosophy based on Jason [8] *'A review that has a clearly defined purpose, a question that describes search approach, stating exclusion and inclusion criteria, generating a qualitative appraisal of articles.* This definition deems findings to be transparent enough for the readers to corroborate any further study. As presented in Table 1 below, the diversity approach has been employed from Okoli [9].

Table 1: The Diversity Approach Processes [9]

Process	Description
Research Purpose Statement	The goals are clearly identified
Research Protocol Development	Including the scope, the strategy, and the result analysis are being stated
Literature Retrieve	Electronic search is being done
Data Assessment	The papers are being scored following the evaluation matrix
Result Reporting	The results are being extracted into the matter of facts
Dissemination	Publish in the form of academic journal for the contribution to the knowledge field

2.2 Evaluation Stages

This section includes translation of the top twenty most cited papers into a graphical representation to enable numerical analysis as per each IR4.0 technology enablers to gain a real idea from an academic perspective.

3. Result

The action taken is as per the Purpose Statement, the Protocol Development, Literature Retrieve, Data Assessment, Data Report, and Result Dissemination, as depicted in Table 2 below.

Table 2: Action Taken According to Each Process

Process	Action Taken
Research Purpose Statement	• To understand how well Data Analytics is being adopted by lean philosophy • To propose the solution from the IR4.0 perspective by filling the research gap
Research Protocol Development	As referred to Table 3: The Inclusion and Exclusion for The Research Protocol Development
Literature Retrieve	By the utilization of Scopus Academic Database • Inserting 'Lean Manufacturing' & 'Industry 4.0' as the keyword • the 'Document' as the default search
Data Assessment	By using the Evaluation Table
Data Reporting	The solution proposal that based upon Simulation
Result Dissemination	Publish in the form of academic journal for the contribution to the knowledge field

Table 3: Inclusion and Exclusion for The Research Protocol Development

Inclusion	Exclusion
• From Scopus academic database	• Any publication before the year of 2011
• Written in English	• Paper based on weak analysis
• Articles published from 2011 to 2021	• Books, online sites, and grey literature; conference paper, reports, working papers from certain group
• Papers based on quantitative and qualitative analysis or both	• Pending publication
• Articles, conference paper, and books	
• Final stage of publication	

Meanwhile, two key principles have been followed for setting the limit: the exclusion and inclusion as listed in Table 3. This not only helps to maintain the standard of the research but also determine the scope pertaining to the overall findings.

3.1 Diversity Study on Industry 4.0

A total of 166 document were identified based on the search. Figure 2 below provides the document breakdown, which clearly shows majority of these to be the conference proceedings versus the articles and books, thereby signifying a lack of exploration pertaining to the impact of Industry 4.0 technologies on the role of LM as well as related tools.

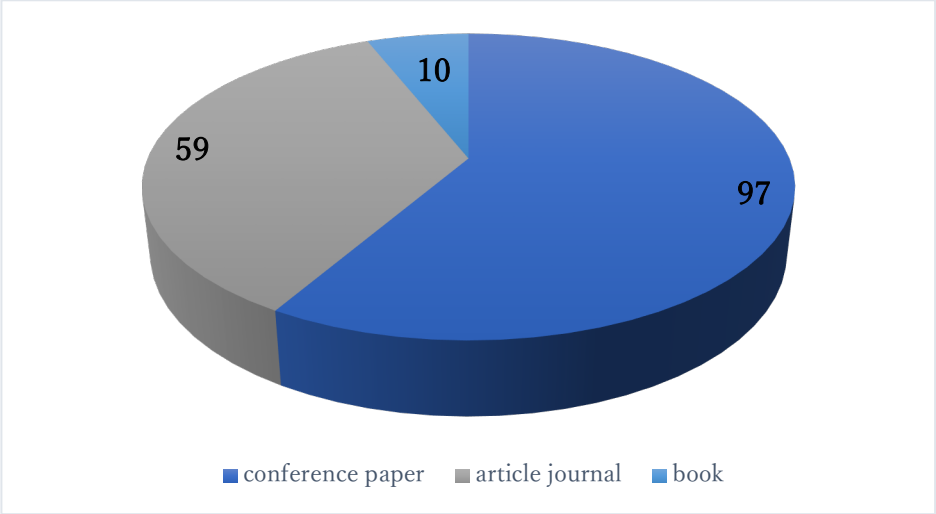

Figure 2: Document Breakdown

In 2016, there were just two publications, and since then the number of documents published each year has kept growing year-over-year, as presented in Figure 3 below. This shows the interest of the researchers in this study field, ensuring a continuous process of knowledge development that can also contribute to the industry. However, even though the LM study is well established and broadly used in the industry, the industry 4.0 is a recent concept, and the oldest document that was published was in 2016. This shows that this field is very much relevant for discussion to generate new knowledge regarding the innovation that can be helpful for the industry

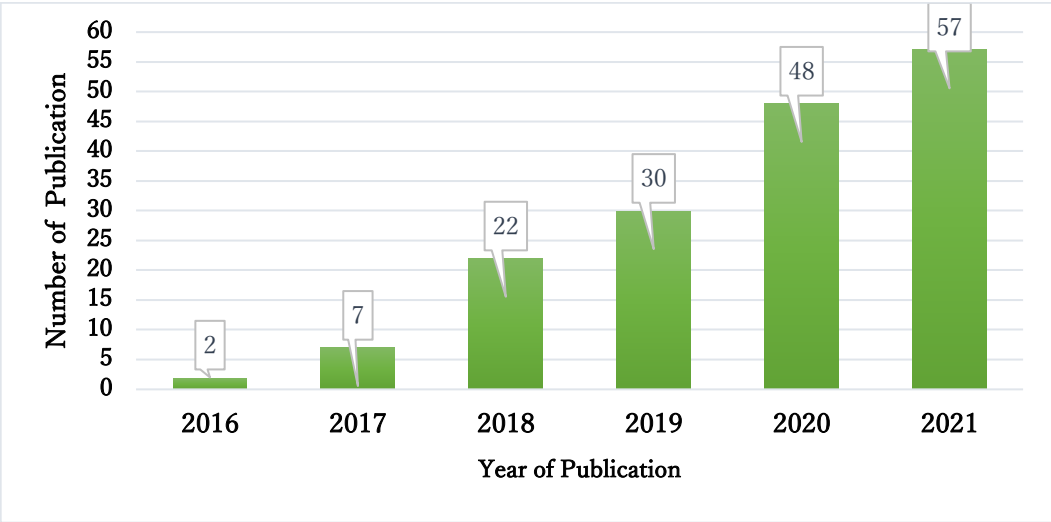

Figure 3: Number of Publication

This list containing 166 documents that were identified was then segmented based on the highest cited documents. The highest 20 of the 166 documents were chosen and then reviewed to confirm their relevance pertaining to the requirements of this study. The paper should be focused on LM implementation along with Industry 4.0 integration, including the theoretical development as well as real case study. All the data from these were translated into a plot graph to determine the numerical insight concerning the IR4.0 technology enablers employed in the industry, as reported in the journals, and demonstrated in Figure 4 below. After simulation, the second most common IR4.0 Technology Enabler, which can be integrated in the industry, is Big Data. Thus, this study continues to concentrate on deciphering IR4.0 with regards to real LM implementation, with a focus on Big Data as the main driver by considering its limitations as well as possible solutions.

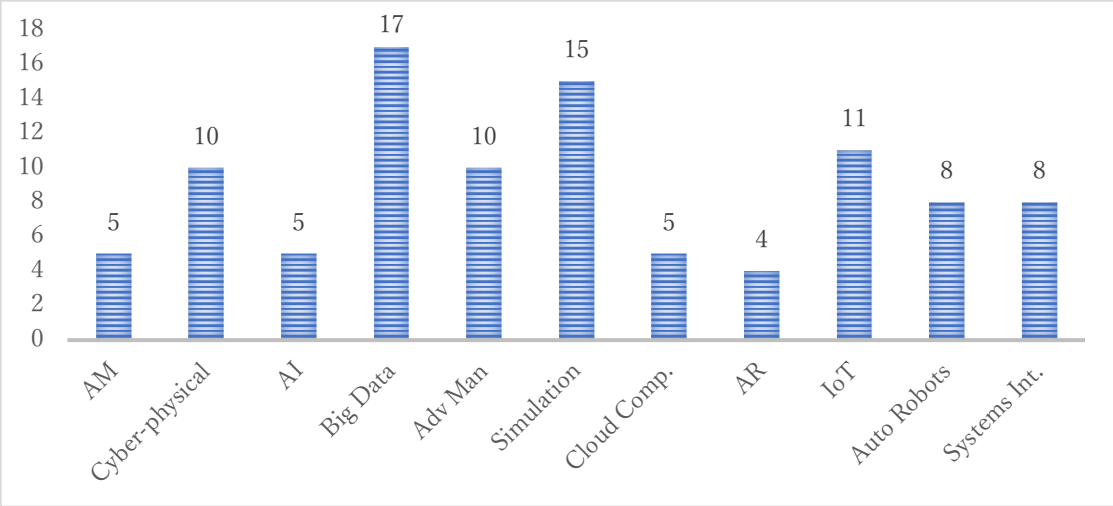

Figure 4: IR4.0 Technology Enablers Utilized in the Industry According to the Document Published

4. Discussion

4.1 Big Data Complexity Issue

For real-time data exchange, the data transmitter (for instance, sensors) is regarded to be a fully automated device that can be employed in the data exchange process. In real-time scenario, synchronising of the data in the cloud storage is done in the processing line. The 'real-time' data interchange includes system cycle time, as well as production structures like product output plans or agendas [10]. Eventually, the real-time method enables swift data exchange procedure via various devices operating simultaneously, generating massive data that need to be dealt

within a short period of time. Regardless, high-velocity, high-volume and high-variety collections of information can yield new insights for decision making [10]. DA, which is the biggest element in Big Data, is used only for tracking and not to improve the overall process [11], [12]. Furthermore, as per Salama [13], since the use of DA still lacks optimal configuration, it results in poor data collection and takes a lot of time. Subsequently, the utilisation DA becomes unproductive and results in impact on the LM production. Thus, a simulation is used for the validating or confirming step and includes combining the data from the database, which prompts DA to be used as a problem-solving technique.

4.2 Simulation as Assistance Proposed

As per the results stated in Figure 4, simulation is the second most common technology employed in the industry. Therefore, the researchers find great interest in employing simulation for the DA. Table 5 shows the quantifying method for providing great insights regarding the simulation applied within the LM application globally.

Table 5: Improvement Made by Simulation

Ref	Year	Improvement	Activity Description
[14]	2020	To increase overall impact of LM	Multiple-level circular diagrams identified the primary contributions of lean tools
[15]	2020	To improve the lean in the automobile assembly industry.	In-depth demonstrations of improved information flow for decision-making are shown. The findings show that using the DSS to support planned and operational operations in digital manufacturing is simple.
[16]	2021	To evaluate the impact of applying lean construction principles	The data were collected to find the best probabilistic density function for each activity duration based on the for-quality test.

Apart from that, the remaining available frameworks pertaining to DA do not offer a stepwise guideline and each framework includes a great number of varying elements for the industry to deploy. Thus, this study puts forward a theoretical formulation pertaining to near-net shape data analysis model, which integrates both key elements of simulation as well as DSS, as presented in Figure 5.

Figure 5: New Proposed Formulation for Decision Support System

5. Conclusion

To summarise, it is crucial that other researchers further assess this study field and explore the IR4.0 technology elements in depth with regards to the LM advancement in the industry. Also, it needs to be noted that there is a rise in the trend of publication year-over-year, demonstrating LM adoption has evolved alongside modernisation of IR4.0.

6. Acknowledgement

The authors are grateful to the Malaysian government and Universiti Teknikal Malaysia Melaka (UTeM) for funding the research via grant FRGS/1/2020/TK0/UTEM/2/42.

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